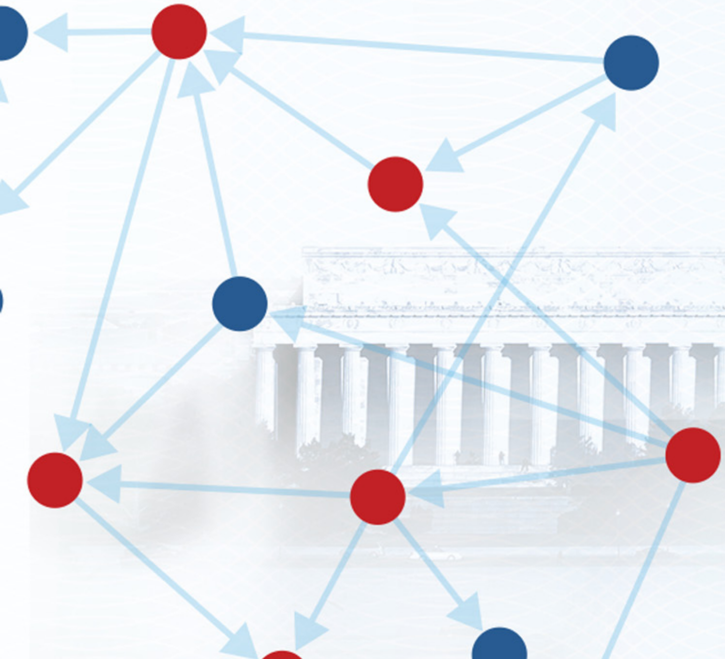
BAYESIALAB



Knowledge Elicitation & Geopolitical Reasoning Under Extreme Uncertainty

Today’s Agenda

Part I

- Introduction
- Methodological Motivation: No Data
- Dimensions of Reasoning
- The Rationale for Bayesian Networks
- Introductory Example
    - Where is my bag?
- Coffee Break

Today's Agenda

Part II: Case Study & Knowledge Elicitation Exercise

- Background for Case Study
    - Territorial Disputes in the South China Sea
    - Chinese Naval Base on Hainan Island
    - Submarine Communication Limitations
- Case Study
    - Missing U.S. Submarine
- The Bayesia Expert Knowledge Elicitation Environment (BEKEE)
- Knowledge Elicitation Exercise
- Decision Optimization

120 min.

Disambiguation

BAYESIA

Your Decision Partner

Our Company

BAYESIALAB

Our Product

The Paradigm

BAYESIAN NETWORKS*

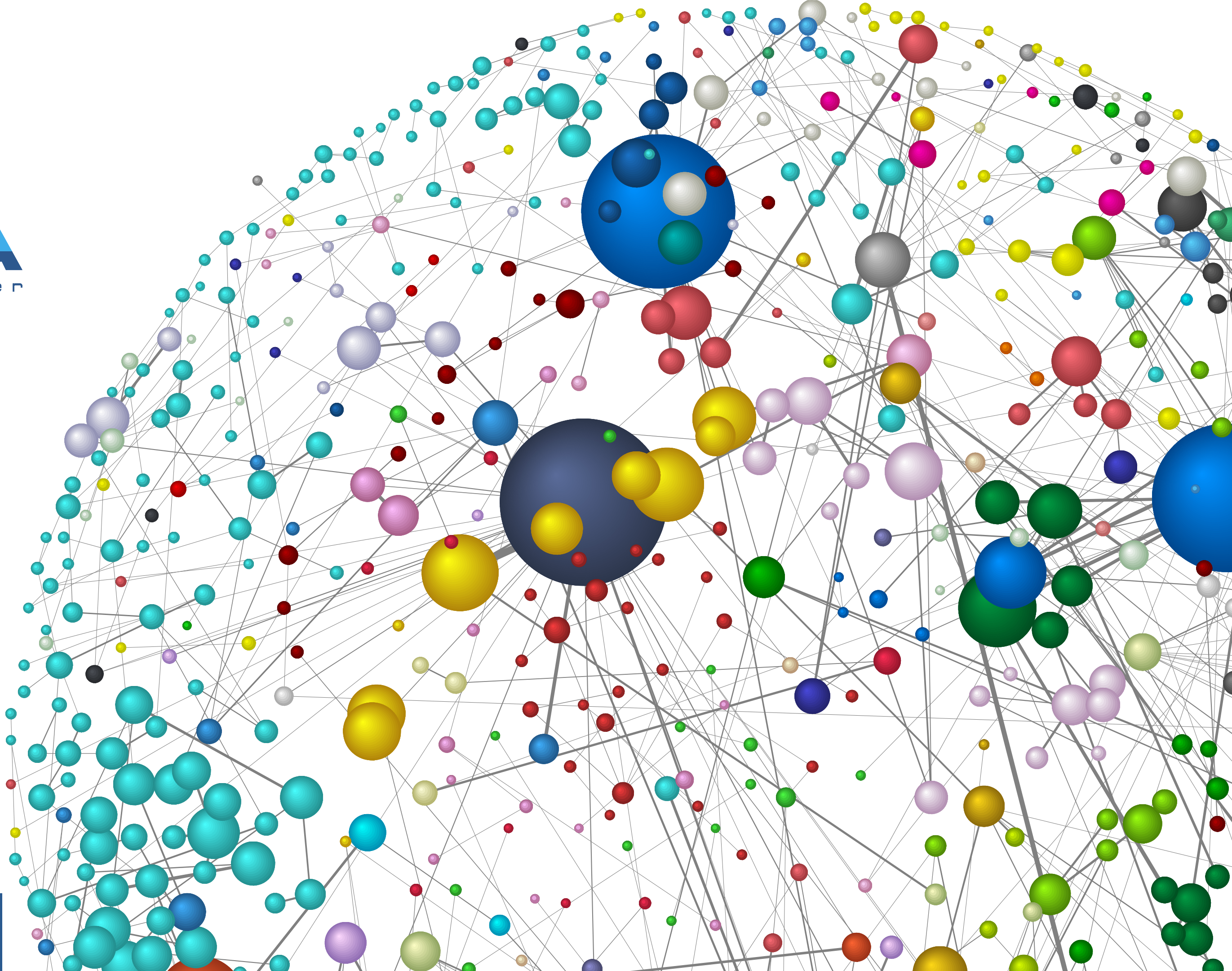
Judea Pearl
Cognitive Systems Laboratory
Computer Science Department
University of California, Los Angeles, CA 90024
judea@cs.ucla.edu

Bayesian networks were developed in the late 1970's to model distributed processing in

BAYESIA

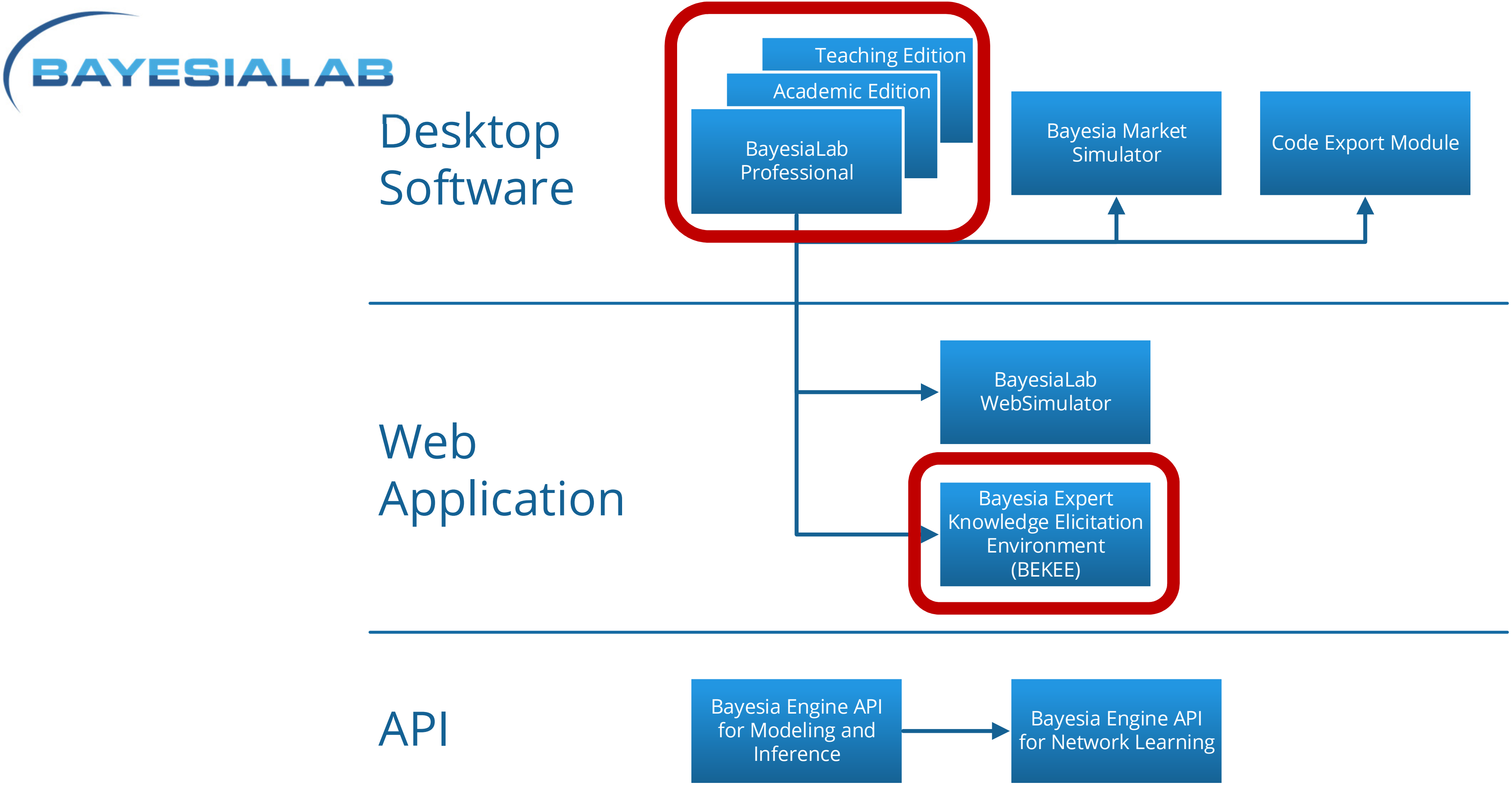
Your Decision Partner

Co-founded in 2001 by Dr. Lionel Jouffe & Dr. Paul Munteanu



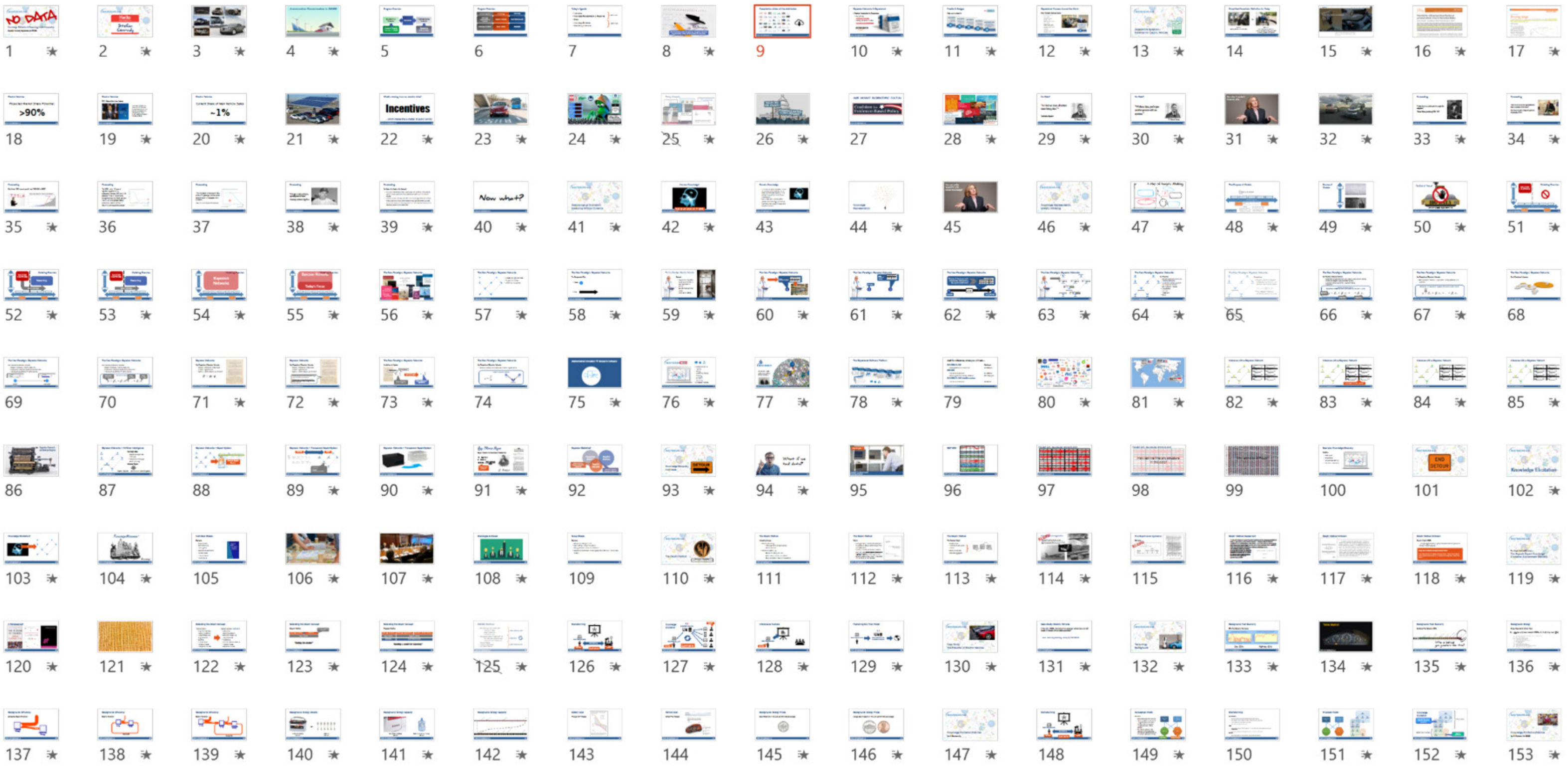
BayesiaLab.com

BAYESIALAB


BAYESIALAB
Desktop Software
Teaching Edition
Academic Edition
BayesiaLab Professional
Bayesia Market Simulator
Code Export Module
Web Application
BayesiaLab WebSimulator
Bayesia Expert Knowledge Elicitation Environment (BEKEE)
API
Bayesia Engine API for Modeling and Inference
Bayesia Engine API for Network Learning

U.S. ARMY
NASA
Booz | Allen | Hamilton
THE WORLD BANK
GEORGETOWN UNIVERSITY
DASSAULT AVIATION
LOCKHEED MARTIN
bp
charles SCHWAB
ArcelorMittal
groupm
WPP
THE pert GROUP
gsk GlaxoSmithKline
UNIVERSITY of VIRGINIA
RENAULT
sodexo
USGS science for a changing world
NYU
DELL
Lilly
Mu Sigma
DO THE MATH
EADS
Holiday Inn
SONY
IHG InterContinental Hotels Group
Unilever
synovate Research reinvented
SOCIETE GENERALE
STANFORD UNIVERSITY
BBDO
HYATT
NYU Langone MEDICAL CENTER
GfK
Nestlé
Fractal
NTT
MAi
Firmenich
National Analysts WORLDWIDE RESEARCH CONSULTING
SAMSUNG
GP Georgia-Pacific
RUTGERS THE STATE UNIVERSITY OF NEW JERSEY
FDA
Cargill
eDF
Ipsos
McGill
P&G
CDC
eni
Hilton HOTELS & RESORTS
LANCASTER UNIVERSITY
VirginiaTech Invent the Future
orange
Burke SINCE 1931
DGA
SNCF
SAINT-GOBAIN
Polk
IMRB international
CATERPILLAR
AIRBUS
VA
Microsoft
Team Detroit
sanofi pasteur
tns
SMUCKER'S
MillwardBrown
American Diabetes Association. Cure • Care • Commitment
MARS
Deloitte.
PENNSTATE 1855
ACXIOM
cancer care ontario | action cancer ontario
UCLA
L'ORÉAL
FEDERAL AVIATION ADMINISTRATION
Rotman UNIVERSITY OF TORONTO
SAFRAN
intel
AIRFRANCE
NeimanMarcus
reperes
VANDERBILT UNIVERSITY
TOTAL
LSU LOUISIANA STATE UNIVERSITY
nielsen
McKinsey&Company
Northwestern Mutual

Slides and networks will be available



Bayesian Networks & BayesiaLab

A Practical Introduction for Researchers

- Free download:
  www.bayesia.com/book
- Hardcopy available on Amazon:
  http://amzn.com/0996533303

20,000
Downloads

Seminar Credits

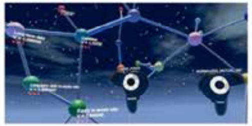
Seminar Credits

Please check in!

718167964896578277001

Event

Free Seminar in Boston: Knowledge Discovery with Bayesian Networks and Virtual Reality



Date+Time

Friday, January 19, 2018 from 1:00 PM to 4:00 PM (EST)

Location

CIC Boston—Lighthouse West
50 Milk Street
20th Floor
Boston, MA 02109

Payment Status

Free Order

Order Info

[illegible]

Type

Seminar: Knowledge Discovery with Bayesian Networks and Virtual Reality

Q&A

Anytime!

No Data!

Motivation


RUSSELL GLASS · SEAN CALLAHAN
THE
BIG DATA
DRIVEN
BUSINESS
O'REILL
Data
Driven
Creating a Data C
DATA
DRIVEN
Data-Driven
Decision-Making
increasing sales with
DATA - DRIVEN
MARKETING
$
$
$
$
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loginradius
5 Steps To Powering
Data Driven Decision Makin
Data
driven
decisions
DATA-DRIVEN decisions in a
FORTUNE 500
MAKING
DATA-DRIVEN
DECISIONS
with
+ableau
+
GET #DATADRIVEN
THE DATA-DRIVEN
FUTURE
Data-Driven
Marketing
DataDriven
Business
stefan.conrady@bay

No Data?

"In God we trust, all others must bring data."*

*attribution disputed

W. Edwards Deming

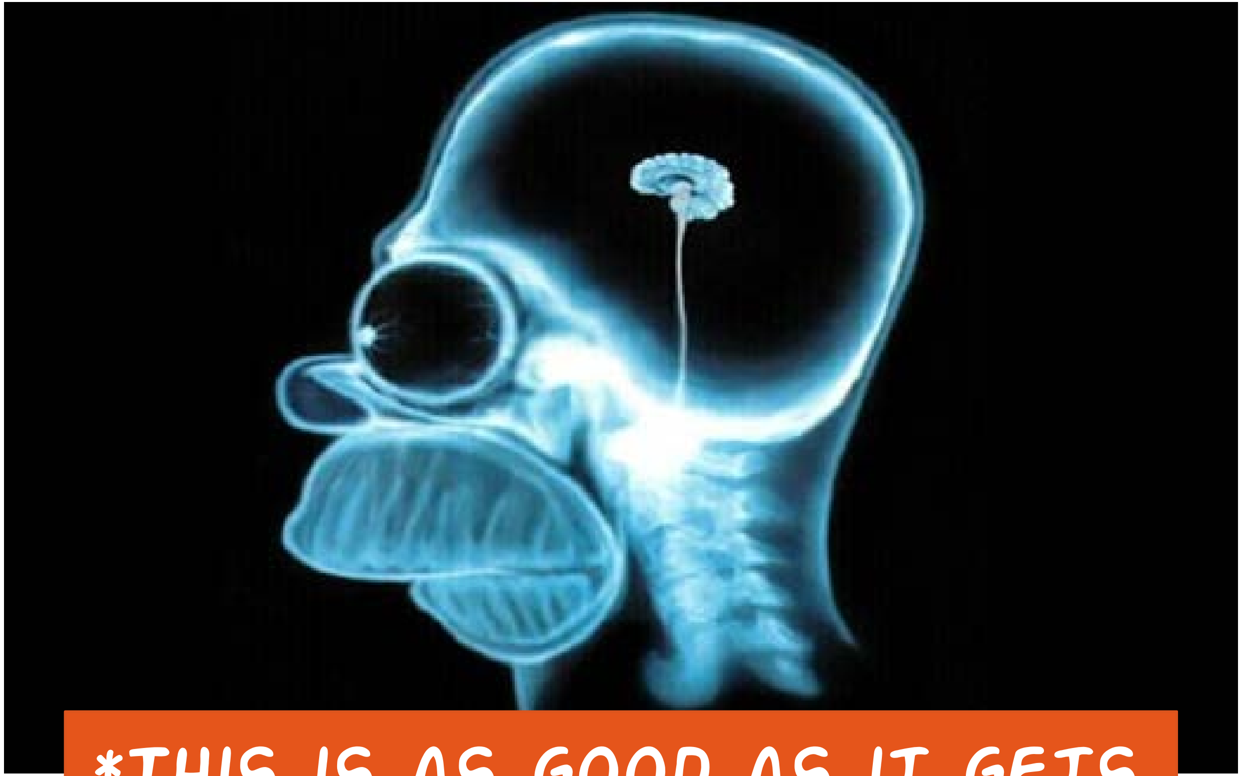

But what if we don’t
have any data…

No Data?

"Without data, you're just another person with an opinion."

W. Edwards Deming

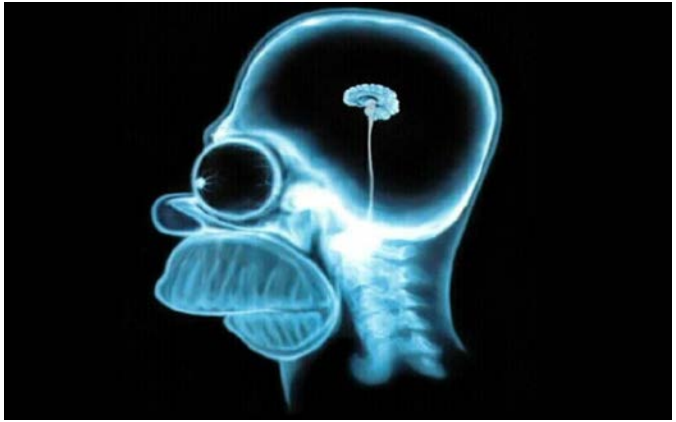
...just another opinion*



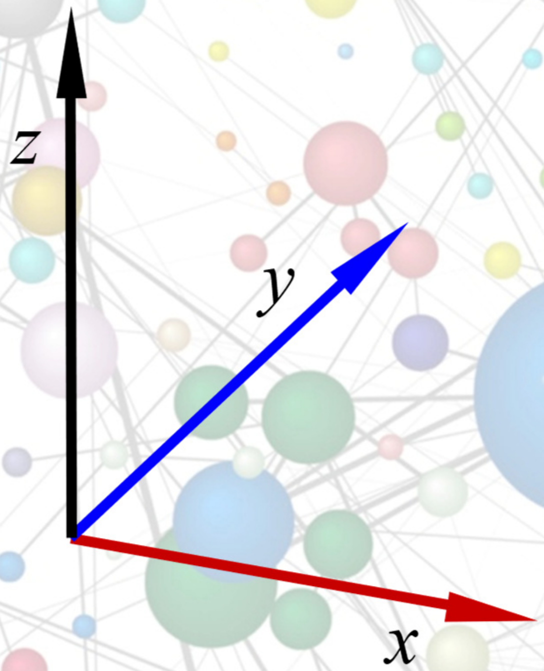
*THIS IS AS GOOD AS IT GETS.

Just Another Opinion or Domain Knowledge?

- In this day and age of "Big Data," we may be led to believe that facts can only be established from data, especially in the context of a scientific inquiry. This is a misconception.
- Even without data, humans do often possess useful knowledge, qualitative or quantitative, tacit or explicit, about many aspects of the world.



How can we be “scientific” with opinions?

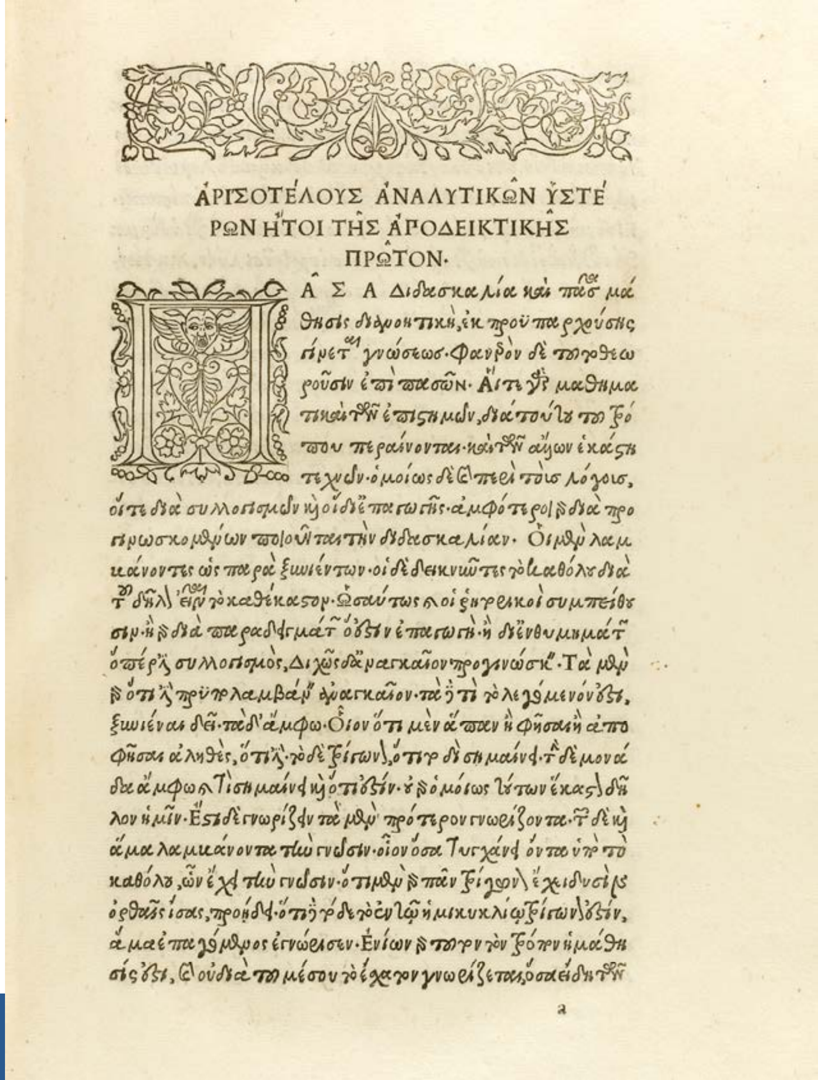


Dimensions of Reasoning

A Map of Analytic Modeling & Reasoning

Deductive Logic

Aristotle (384-322 BC)


ΑΡΙΣΤΟΤΕΛΟΥΣ ΑΝΑΛΥΤΙΚΩΝ ΥΣΤΕΡΩΝ ΗΤΟΙ ΤΗΣ ΑΠΟΔΕΙΚΤΙΚΗΣ ΠΡΩΤΟΝ.

Deductive Logic

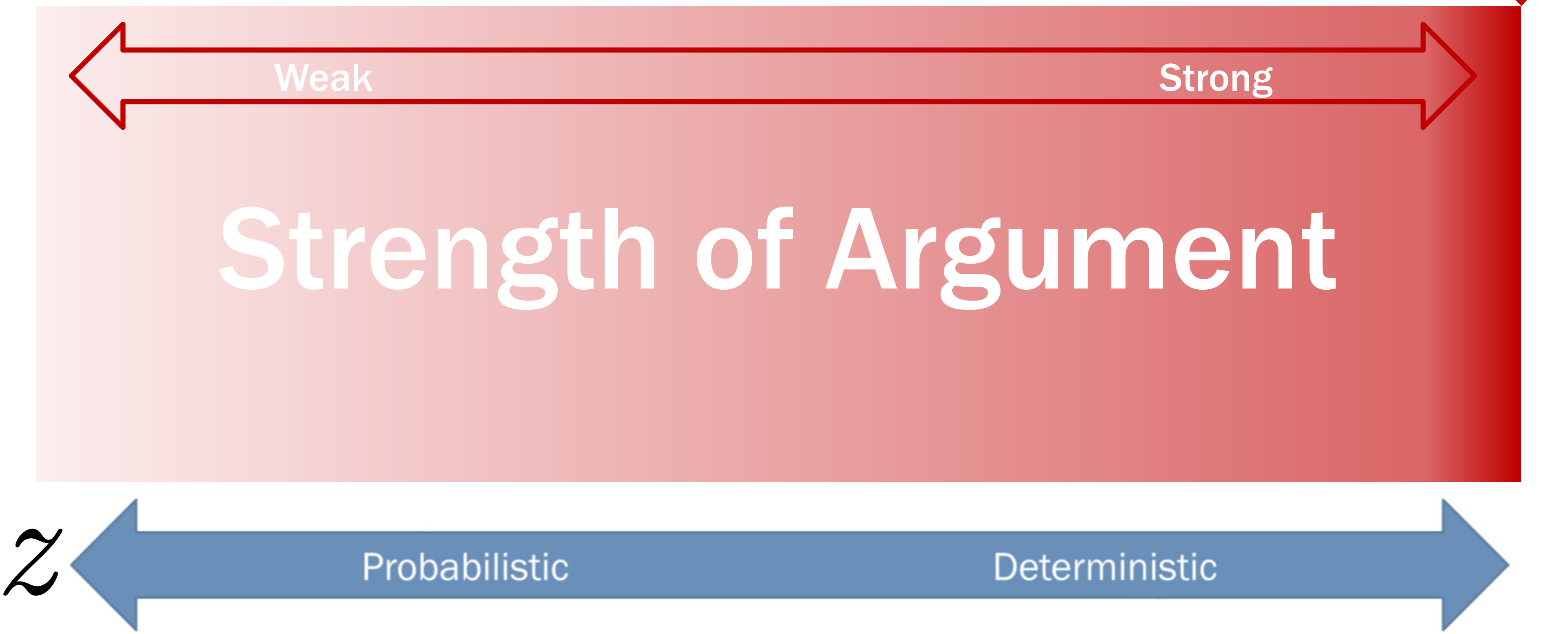
Limitations of Logic

"Classical logic has no explicit mechanism for representing the degree of certainty of premises in an argument, nor the degree of certainty in a conclusion, given those premises."

J. Williamson, Handbook of the Logic of Argument and Inference: The Turn Toward the Practical

Logic is not enough!

Inductive vs. Deductive Logic



2000 Years Later…

Bayes' Theorem for Conditional Probabilities

H: *Hypothesis*

E: *Evidence*

$$P(H \mid E) = \frac{P(E \mid H)\,P(H)}{P(E)}$$

"Probability of H given E"

T. Bayes.

1763
PHILOSOPHICAL TRANSACTIONS

[370]

quodque ſolum, certa nitri ſigna præbere, ſed plura concurrere debere, ut de vero nitro producto dubium non relinquatur.

LII. *An Eſſay towards ſolving a Problem in the Doctrine of Chances. By the late Rev. Mr.* Bayes, *F. R. S. communicated by Mr.* Price, *in a Letter to* John Canton, *A. M. F. R. S.*

Dear Sir,

Read Dec. 23, 1763. I Now ſend you an eſſay which I have found among the papers of our deceaſed friend Mr. Bayes, and which, in my opinion, has great merit, and well deſerves to be preſerved. Experimental philoſophy, you will find, is nearly intereſted in the ſubject of it; and on this account there ſeems to be particular reaſon for thinking that a communication of it to the Royal Society cannot be improper.

He had, you know, the honour of being a member of that illuſtrious Society, and was much eſteemed by many in it as a very able mathematician. In an introduction which he has writ to this Eſſay, he ſays, that his deſign at firſt in thinking on the ſubject of it was, to find out a method by which we might judge concerning the probability that an event has to happen, in given circumſtances, upon ſuppoſition that we know nothing concerning it but that, under the ſame circum-

Probabilistic Reasoning

Mathematical Formulation of Probabilistic Reasoning

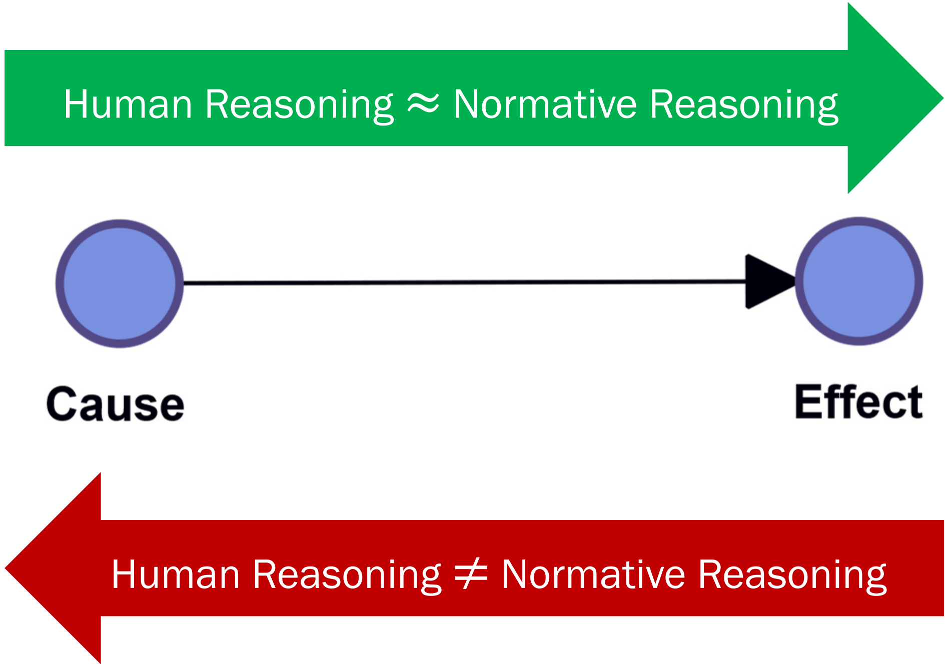
“Bayesian inference is important because it provides a normative and general-purpose procedure for reasoning under uncertainty.”

Inductive Reasoning: Experimental, Developmental, and Computational Approaches, edited by Aidan Feeney and Evan Heit

This is it!

Why is this so important?

Human Cognitive Limitations and Biases Under Uncertainty

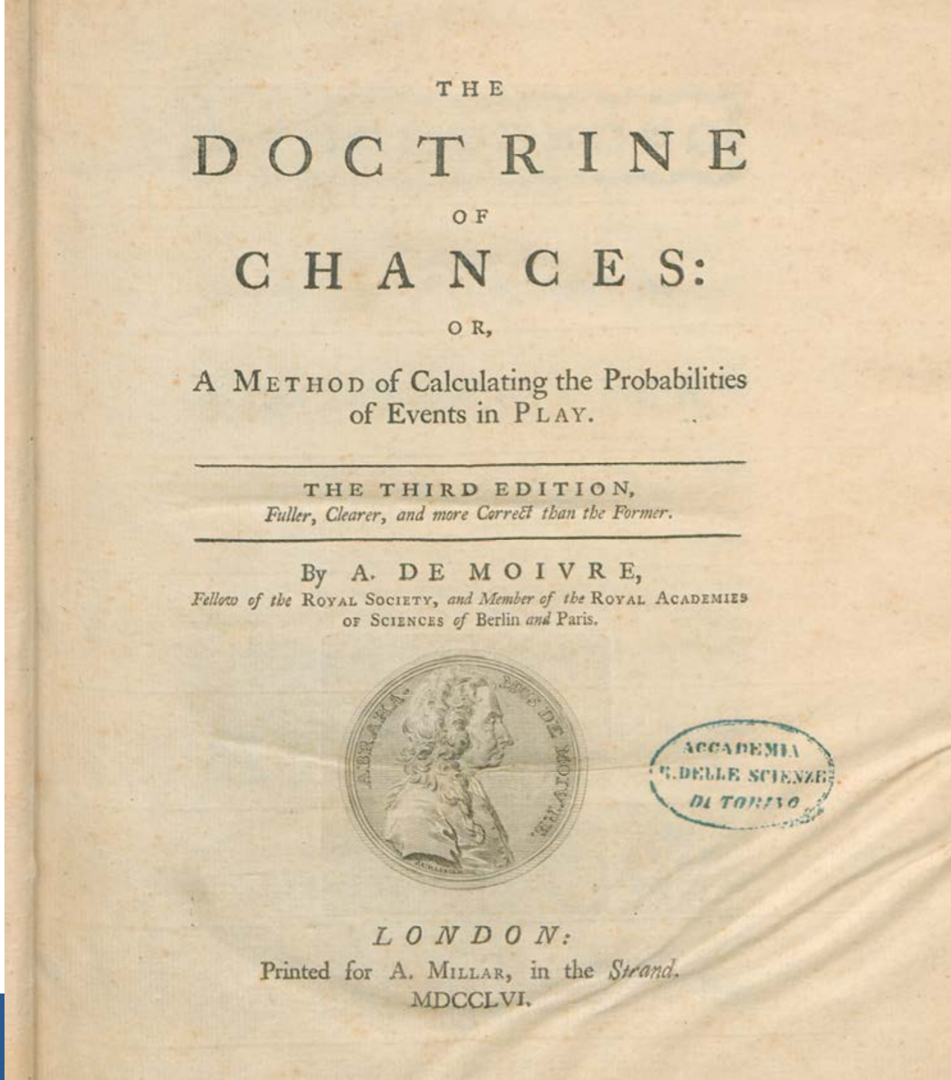


FALLACIES

250 Years Later…

- "…despite the mathematization of probability in the Enlightenment, mathematical probability theory remains, to this very day, **entirely unused** in criminal courtrooms, when evaluating the 'probability' of the guilt of a suspected criminal."

  James Franklin, The Science of Conjecture: Evidence and Probability before Pascal, 2001 The Johns Hopkins Press

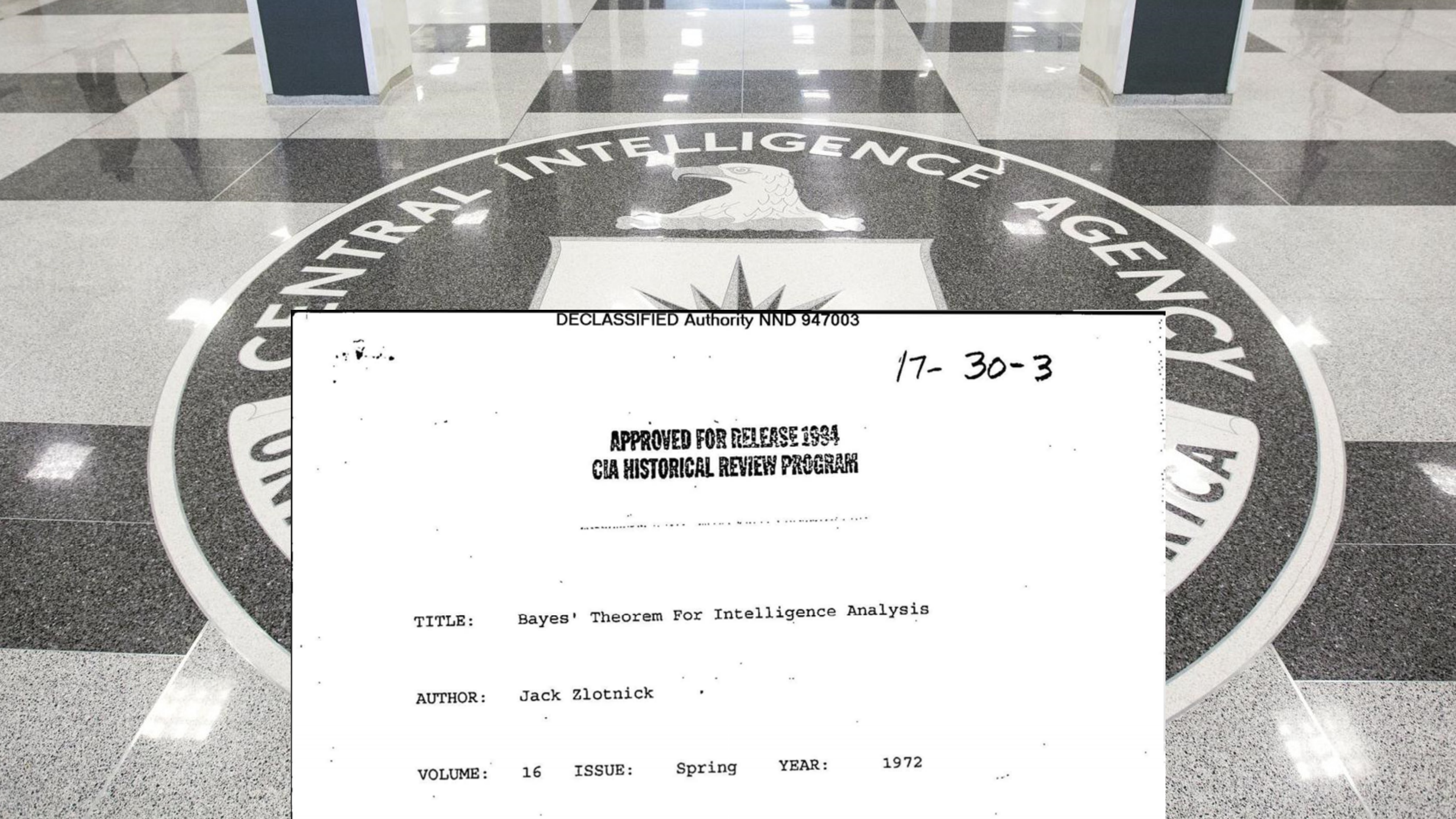


THE
DOCTRINE
OF
CHANCES:
OR,
A METHOD of Calculating the Probabilities of Events in PLAY.

THE THIRD EDITION,
Fuller, Clearer, and more Correct than the Former.

By A. DE MOIVRE,
Fellow of the ROYAL SOCIETY, *and Member of the* ROYAL ACADEMIES OF SCIENCES *of* Berlin *and* Paris.

LONDON:
Printed for A. MILLAR, in the *Strand.*
MDCCLVI.



17- 30-3

TITLE: Bayes' Theorem For Intelligence Analysis

AUTHOR: Jack Zlotnick

VOLUME: 16 ISSUE: Spring YEAR: 1972

Bayesian Inference in Practice?

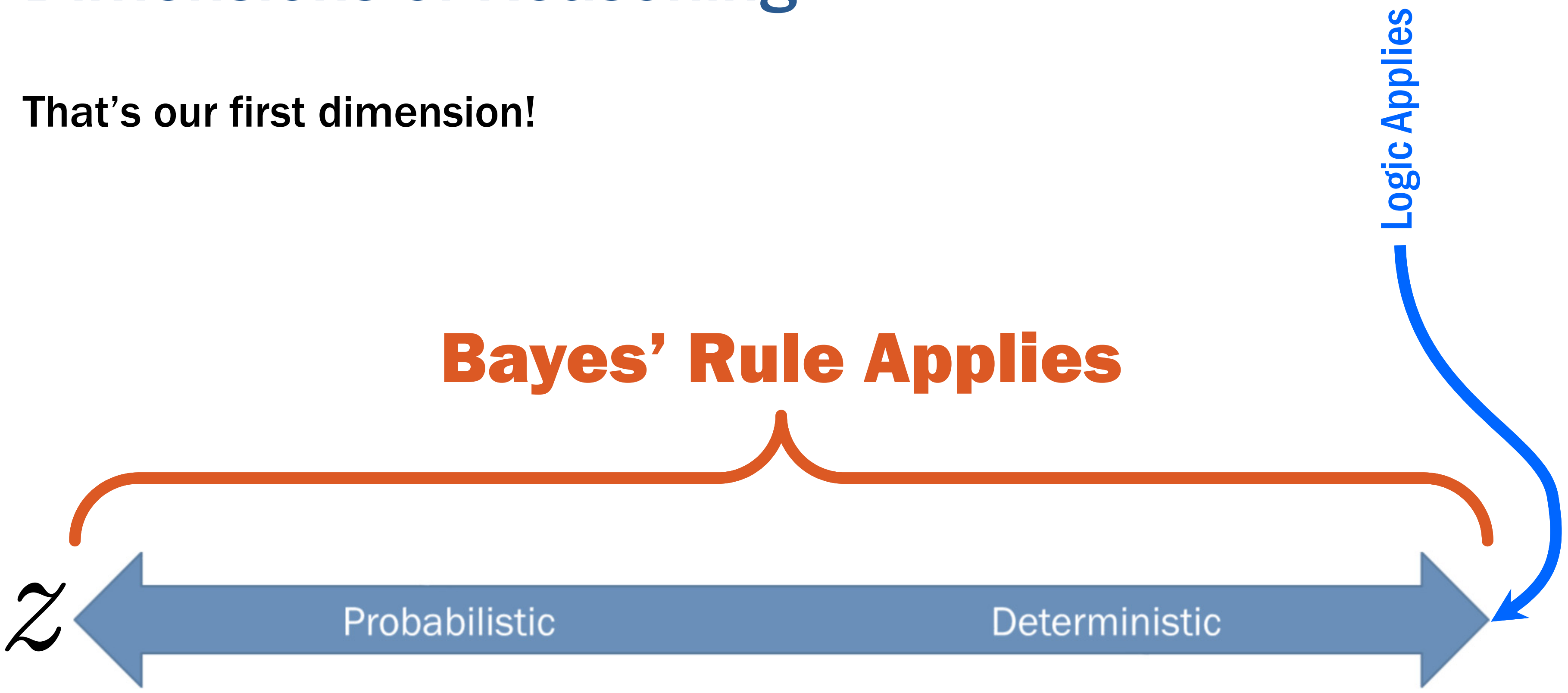
"Due to the highly mathematical nature of Bayesian Decision Analysis, many users will feel uneasy trusting the resulting assessments."

Captain David Lawrence Graves, USAF, Bayesian Analysis Methods for Threat Prediction, MSSI Thesis (Washington: Defense Intelligence College, July 1993)

Seriously?

Dimensions of Reasoning

That's our first dimension!



Dimensions of Reasoning

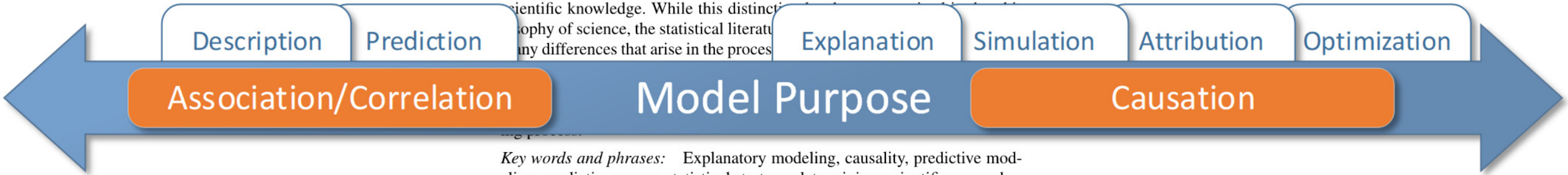
Statistical Science
2010, Vol. 25, No. 3, 289–310
DOI: 10.1214/10-STS330

To Explain or to Predict?

Galit Shmueli

Abstract. Statistical modeling is a powerful tool for developing and testing theories by way of causal explanation, prediction, and description. In many disciplines there is near-exclusive use of statistical modeling for causal explanation and the assumption that models with high explanatory power are inherently of high predictive power. Conflation between explanation and prediction is common, yet the distinction must be understood for progressing ...ientific knowledge. While this distinct... ...ophy of science, the statistical literatu... ...ny differences that arise in the proces...
...ng process.

Key words and phrases: Explanatory modeling, causality, predictive modeling, predictive power, statistical strategy, data mining, scientific research.



x

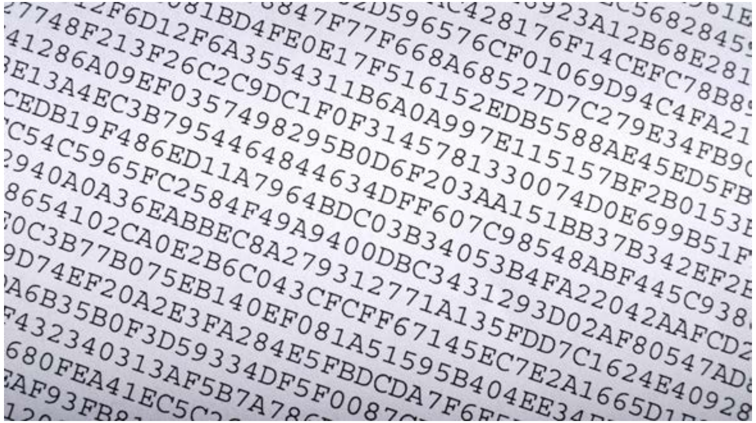
1. INTRODUCTION

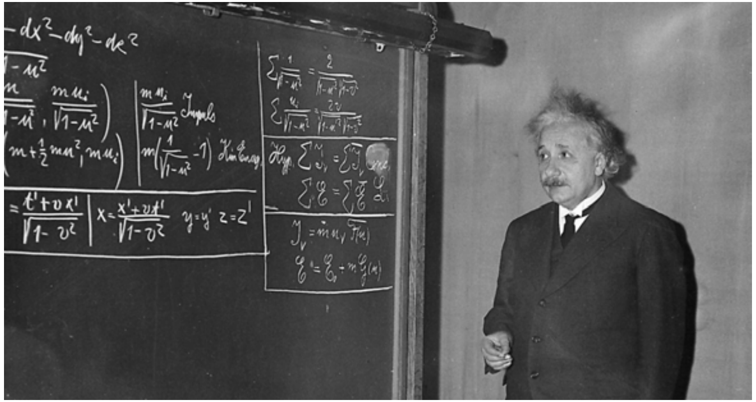
Looking at how statistical models are used in different scientific disciplines for the purpose of theory building and testing, one finds a range of perceptions regarding the relationship between causal explanation and empirical prediction. In many scientific fields such as economics, psychology, education, and environmental science, statistical models are used almost exclu-

focus on the use of statistical modeling for causal explanation and for prediction. My main premise is that the two are often conflated, yet the causal versus predictive distinction has a large impact on each step of the statistical modeling process and on its consequences. Although not explicitly stated in the statistics methodology literature, applied statisticians instinctively sense that predicting and explaining are different. This article

Dimensions of Reasoning

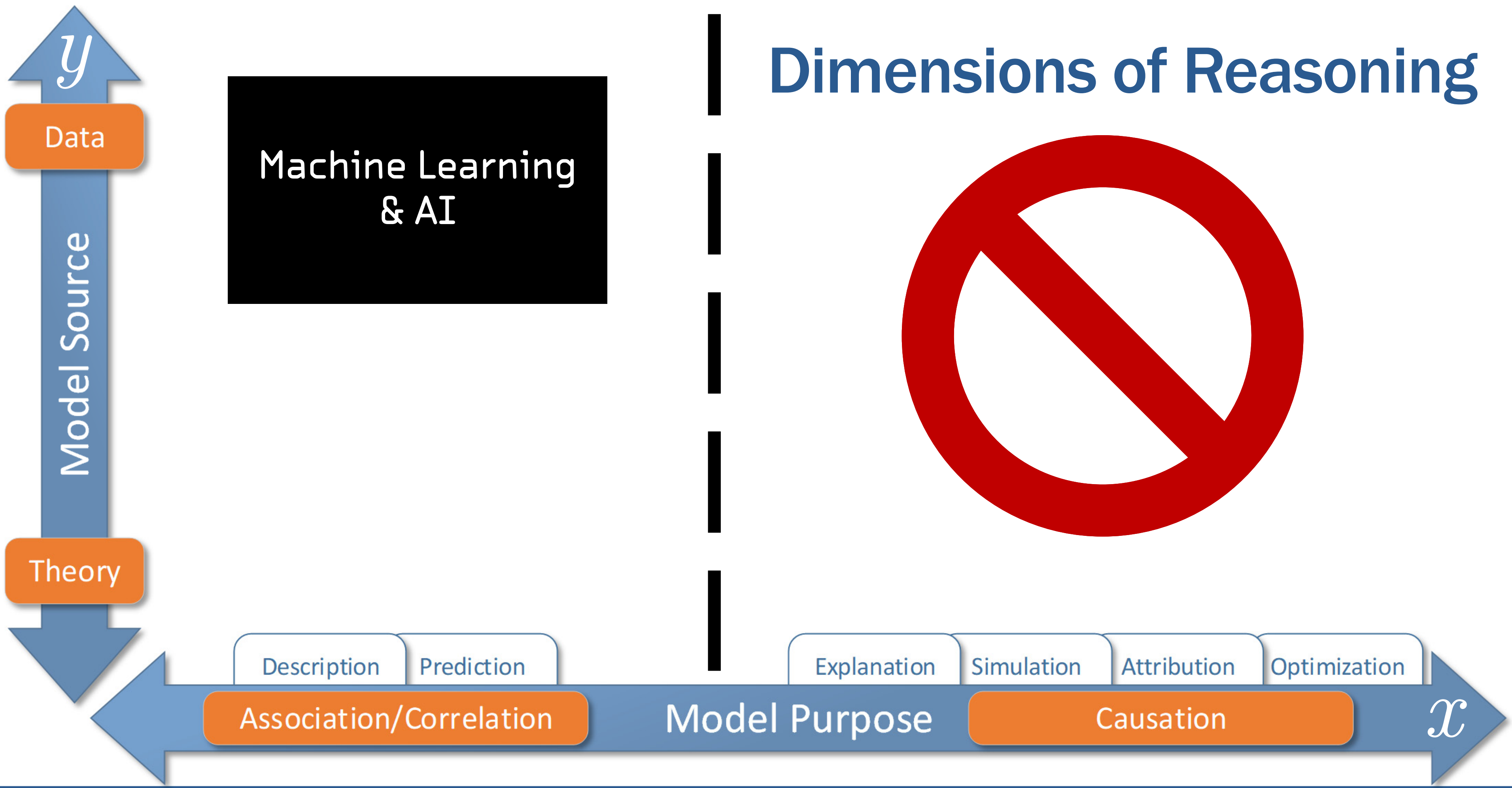
y



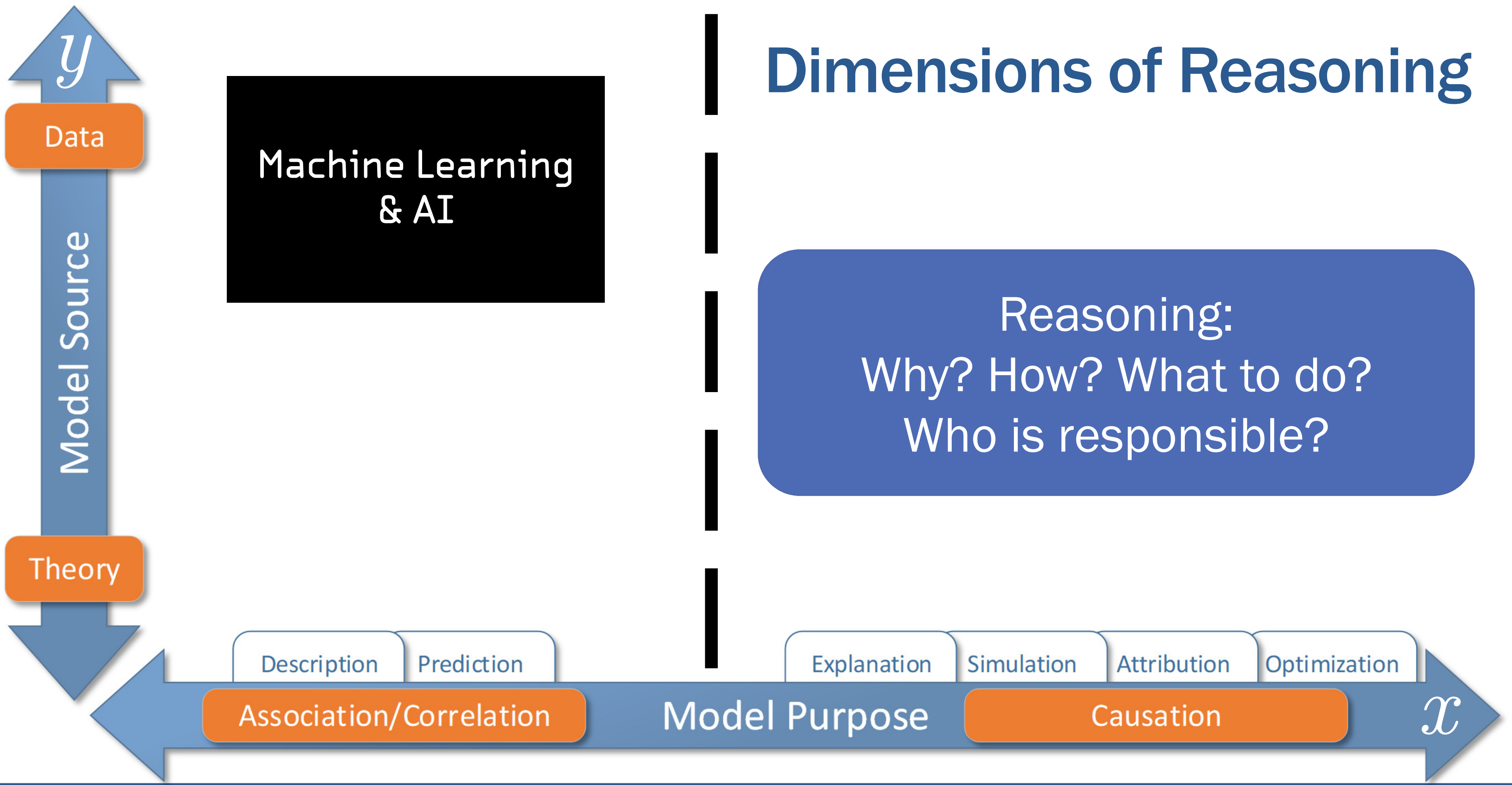


The End of Theory?

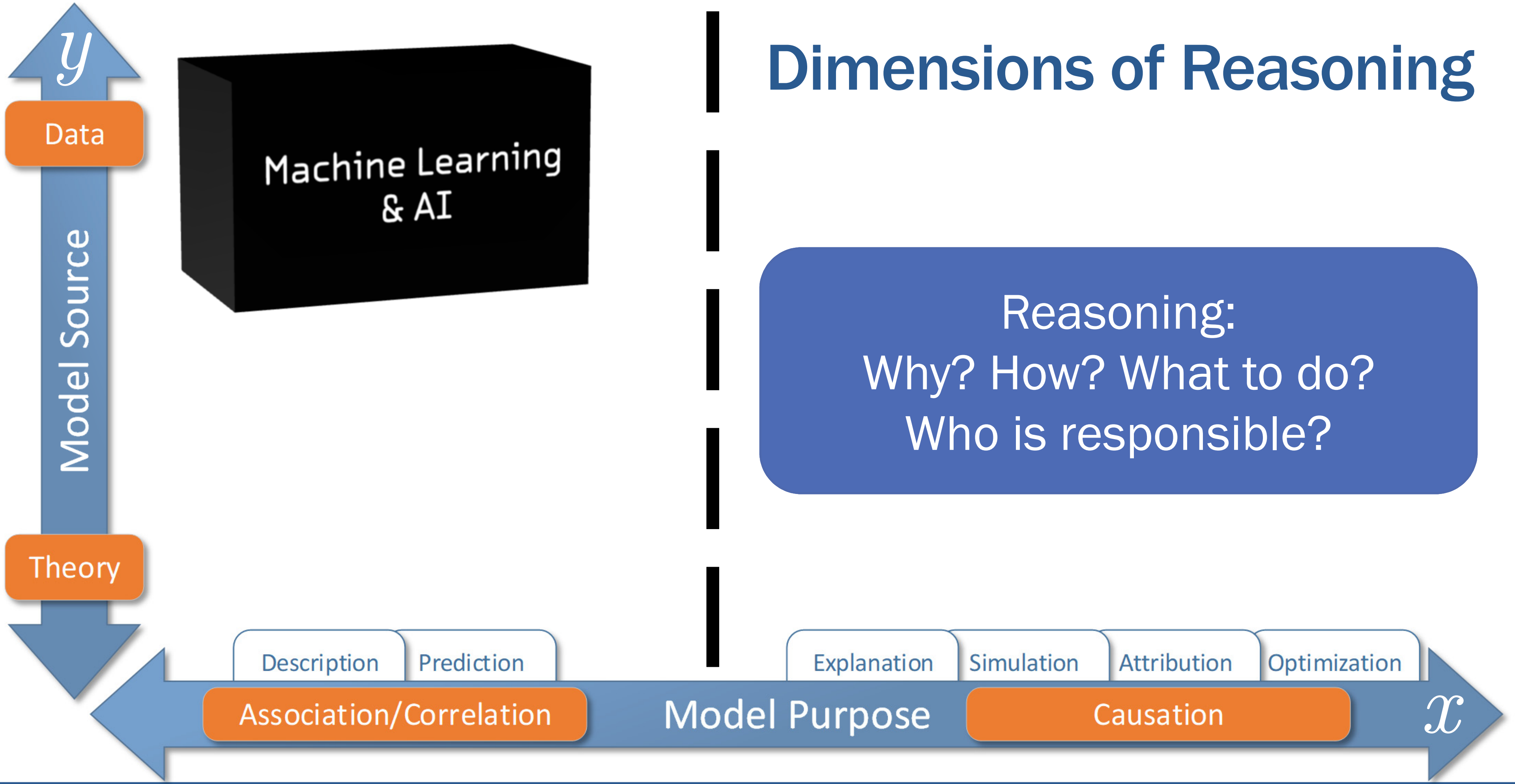
Dimensions of Reasoning



Dimensions of Reasoning



Dimensions of Reasoning



Reasoning:
Why? How? What to do?
Who is responsible?

Dimensions of Reasoning

y

Data

Model Source

Theory

$$y = f(\textcolor{red}{see(x)})$$

“given that I see”

$$y = f(\textcolor{red}{do(x)})$$

“given that I do”

Description | Prediction

Association/Correlation

Model Purpose

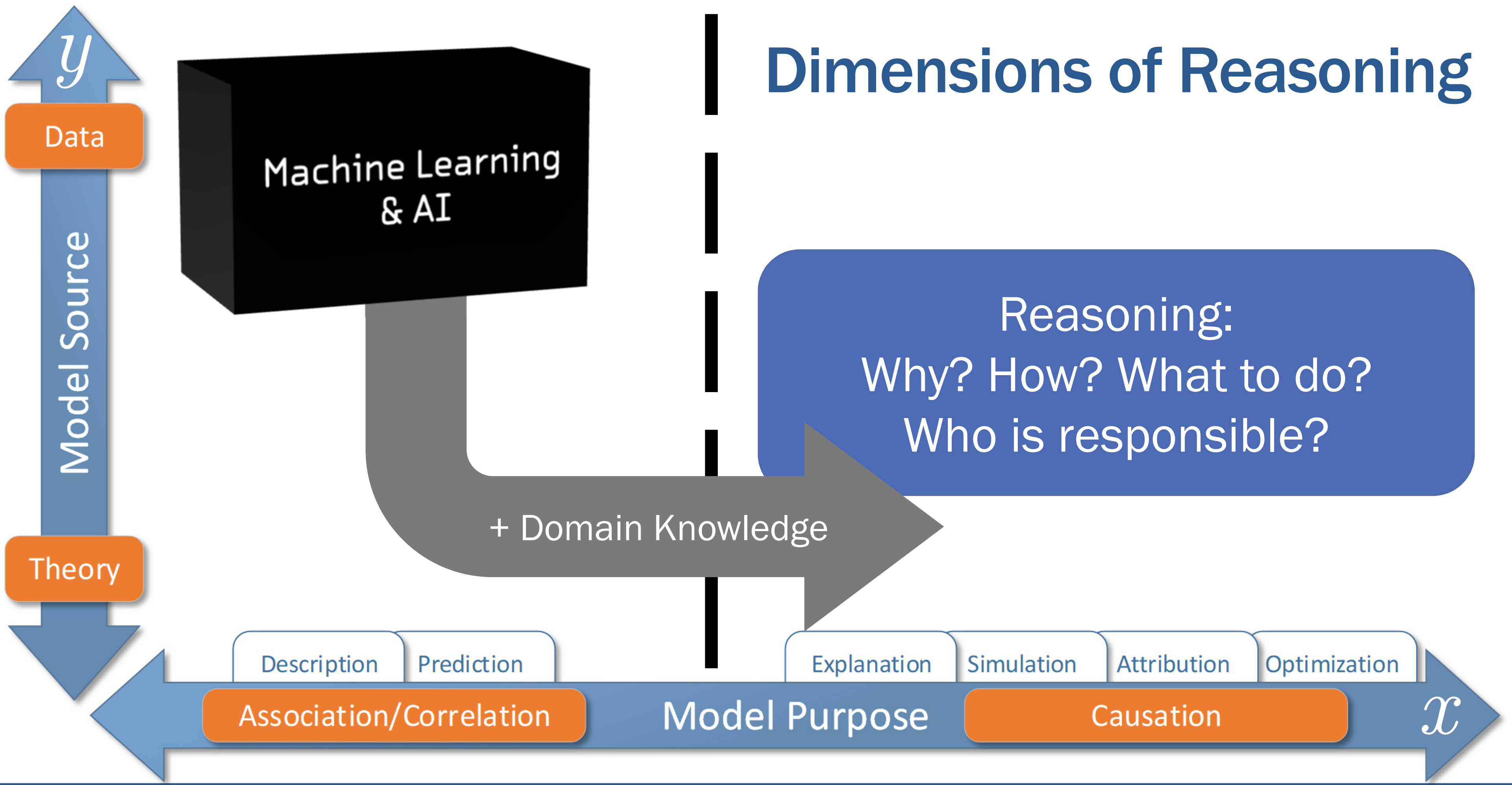
Explanation | Simulation | Attribution | Optimization

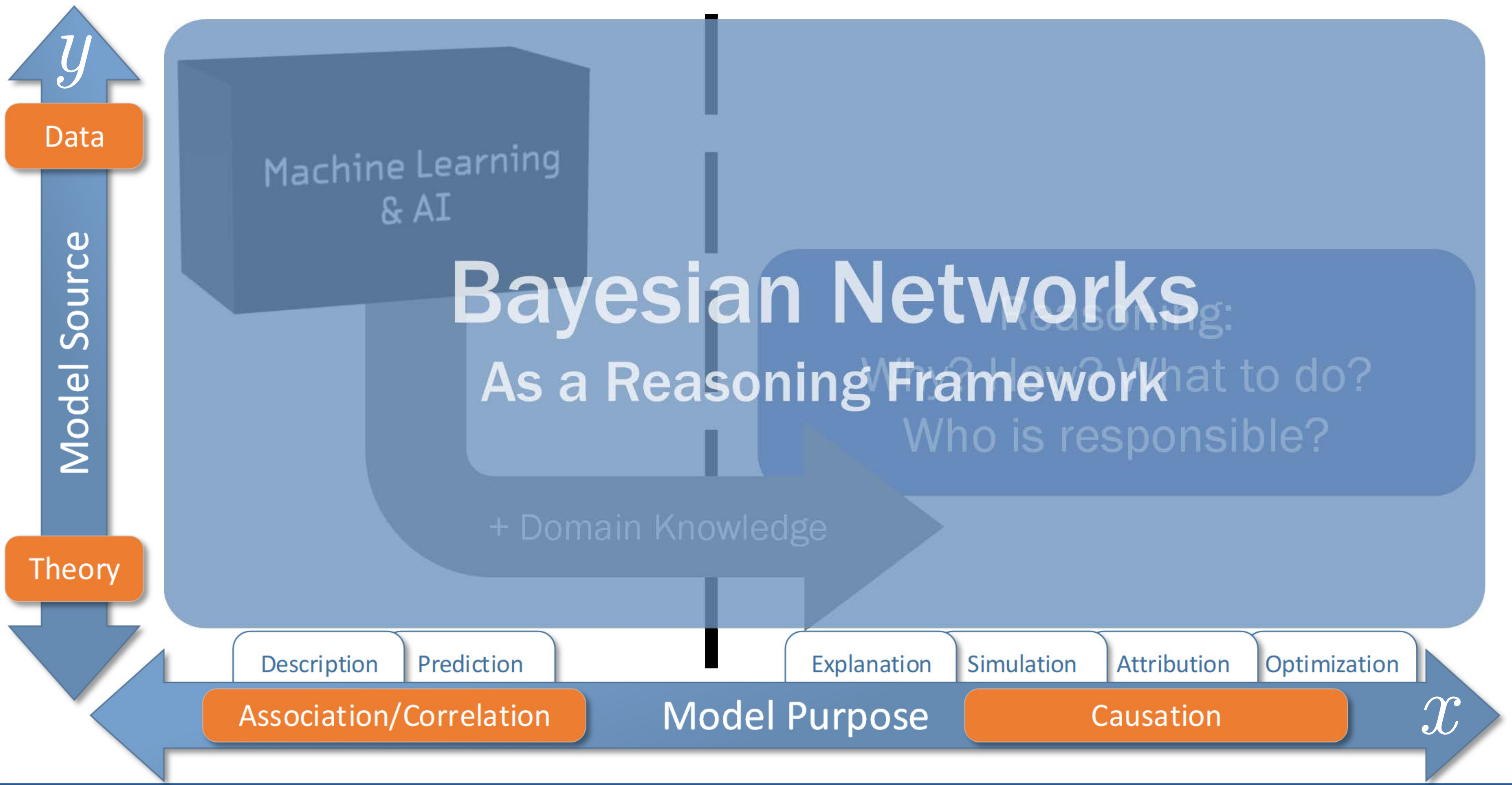
Causation

x

THE FALLACY OF DATA-DRIVEN DECISIONS.

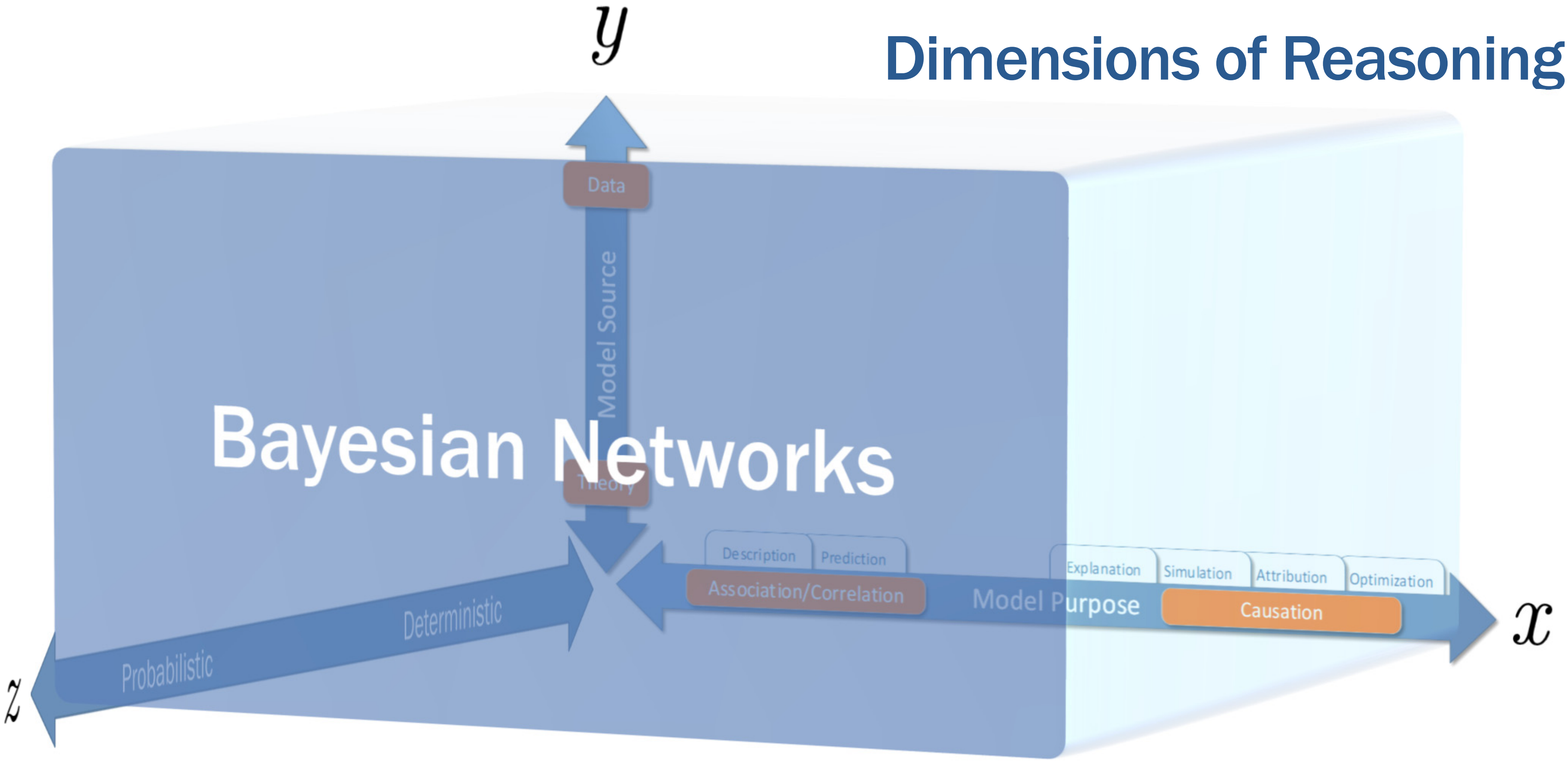
Dimensions of Reasoning





y
Data
Model Source
Theory
Machine Learning & AI
Bayesian Networks
As a Reasoning Framework
Reasoning:
Why? How? What to do?
Who is responsible?
+ Domain Knowledge
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation
x

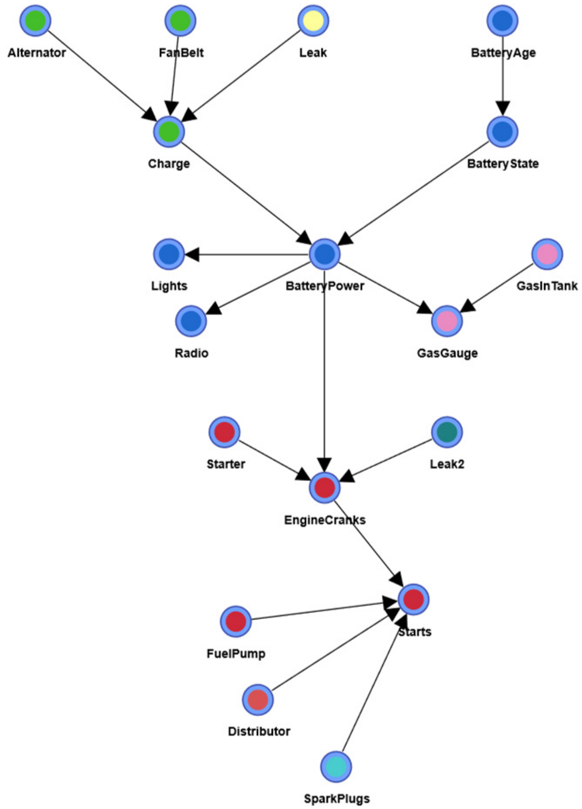
Dimensions of Reasoning



The New Paradigm: Bayesian Networks

The New Paradigm: Bayesian Networks

The New Paradigm: Bayesian Networks



Key Properties

- Compact Representation of the Joint Probability Distribution
- No distinction between dependent and independent variables
- Omni-directional Bayesian inference
- Nonparametric
- Probabilistic
- Causal
- Intuitive
- Scalable

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- Representation (or approximation) of the joint probability distribution of all variables.
- No distinction between dependent and independent variables.
- Numerical and categorical variables are treated identically.
- Nonparametric.

Compare to algebraic formula:
Representation of **one** variable of the joint probability distribution, i.e. y=f(x)

Dependent

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

Independent

Independent

The New Paradigm: Bayesian Networks

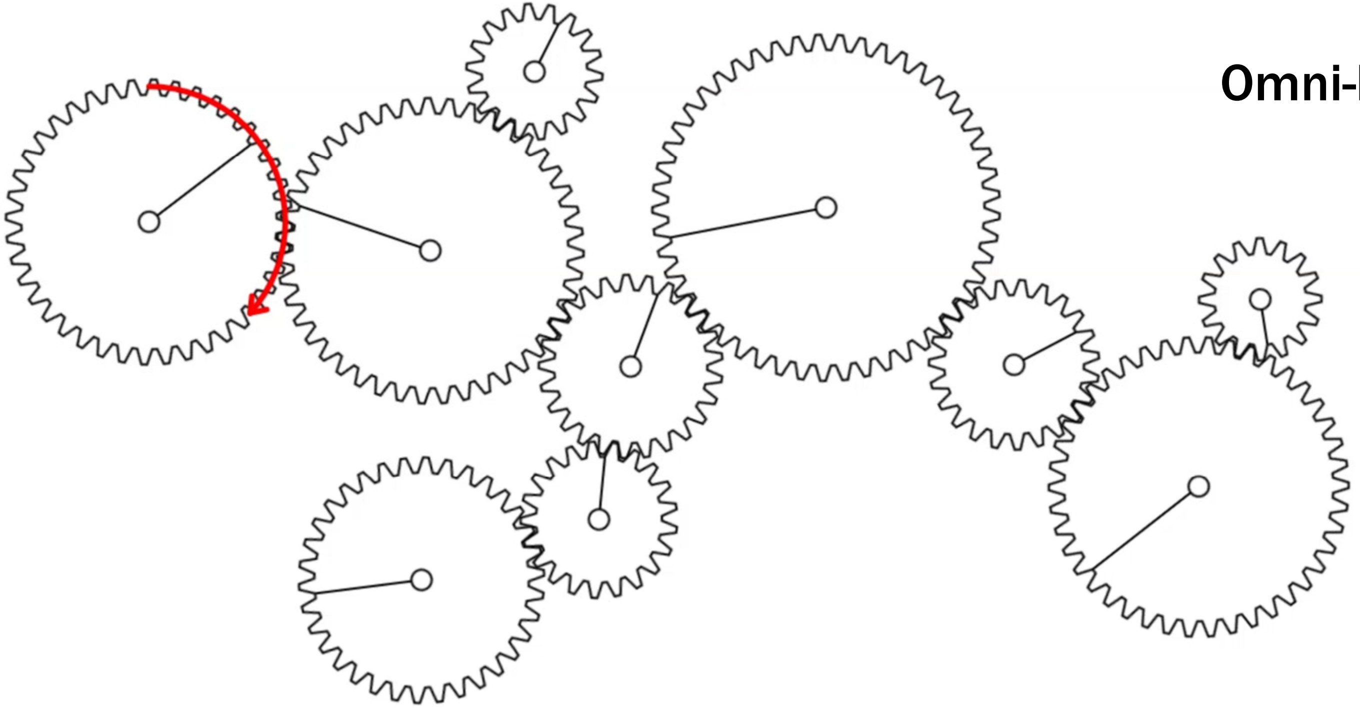
Key Properties of Bayesian Networks

- Omni-directional Inference, i.e. evaluation is always performed in all directions.

Compare to "uni-directional" algebraic formula and human intuition

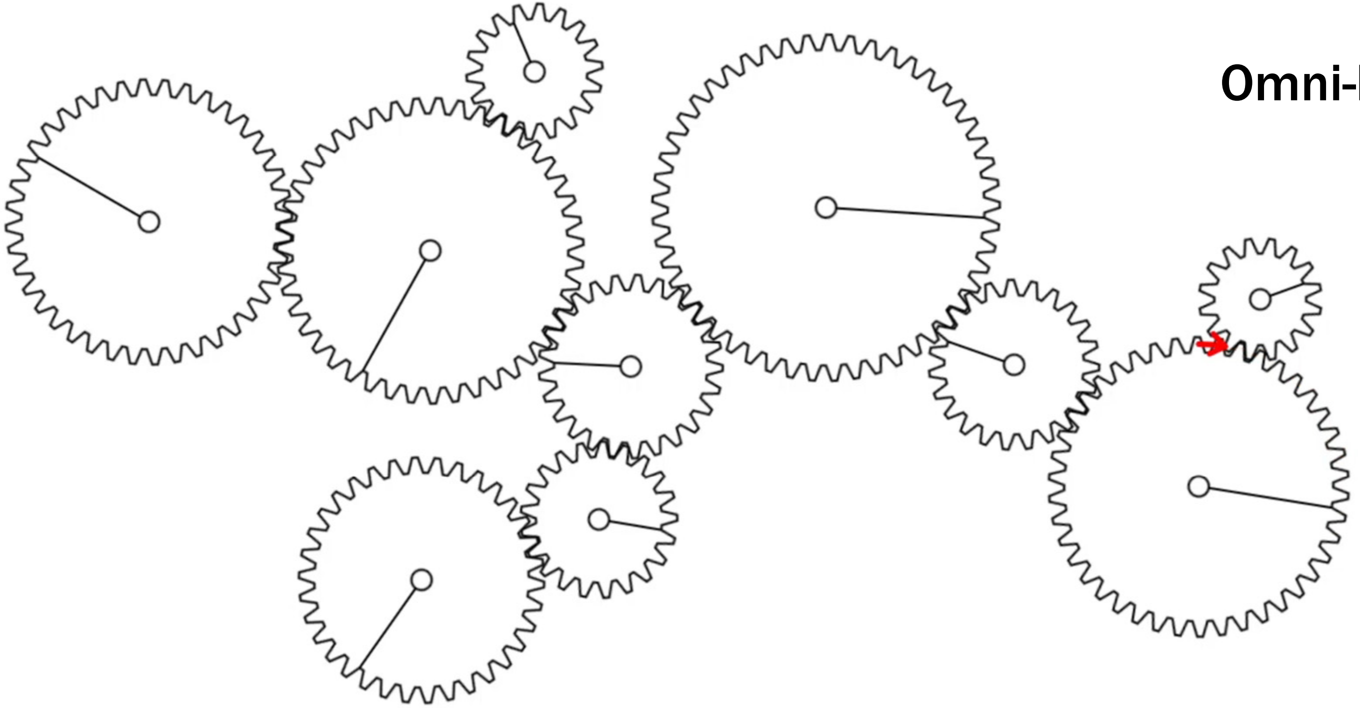
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

Bayesian Networks for Risk Management



Omni-Directional
Inference

Bayesian Networks for Risk Management



Omni-Directional Inference

The New Paradigm: Bayesian Networks

Key Properties of Bayesian Networks

- Bayesian networks are inherently probabilistic.
- Evidence and inference are represented by distributions.
- Inference can be performed with partial evidence.

Compare to algebra

Deterministic Point Estimate

Single Value Input

Single Value Input

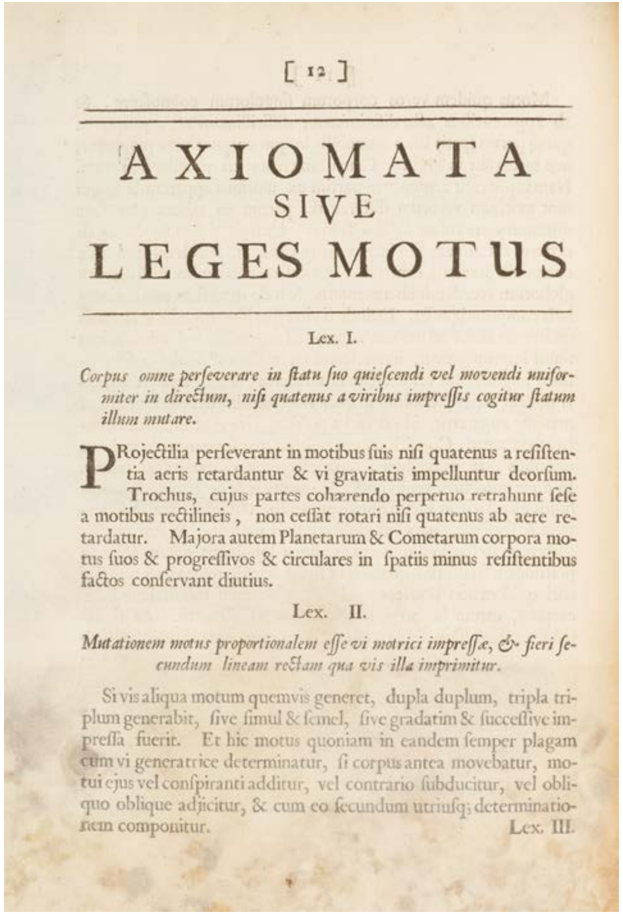
$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

Bayesian Networks

Key Properties of Bayesian Networks

- Bayesian networks can encode causal direction, algebra cannot.
- Example: Newton's Second Law of Motion

$$F = m \cdot a$$



[12]

AXIOMATA
SIVE
LEGES MOTUS

Lex. I.

Corpus omne perſeverare in ſtatu ſuo quieſcendi vel movendi uniformiter in directum, niſi quatenus a viribus impreſſis cogitur ſtatum illum mutare.

PRojectilia perſeverant in motibus ſuis niſi quatenus a reſiſtentia aeris retardantur & vi gravitatis impelluntur deorſum. Trochus, cujus partes cohærendo perpetuo retrahunt ſeſe a motibus rectilineis, non ceſſat rotari niſi quatenus ab aere retardatur. Majora autem Planetarum & Cometarum corpora motus ſuos & progreſſivos & circulares in ſpatiis minus reſiſtentibus factos conſervant diutius.

Lex. II.

Mutationem motus proportionalem eſſe vi motrici impreſſæ, & fieri ſecundum lineam rectam qua vis illa imprimitur.

Si vis aliqua motum quemvis generet, dupla duplum, tripla triplum generabit, ſive ſimul & ſemel, ſive gradatim & ſucceſſive impreſſa fuerit. Et hic motus quoniam in eandem ſemper plagam cum vi generatrice determinatur, ſi corpus antea movebatur, motui ejus vel conſpiranti additur, vel contrario ſubducitur, vel oblique adjicitur, & cum eo ſecundum utriuſq; determinationem componitur.

Lex. III.

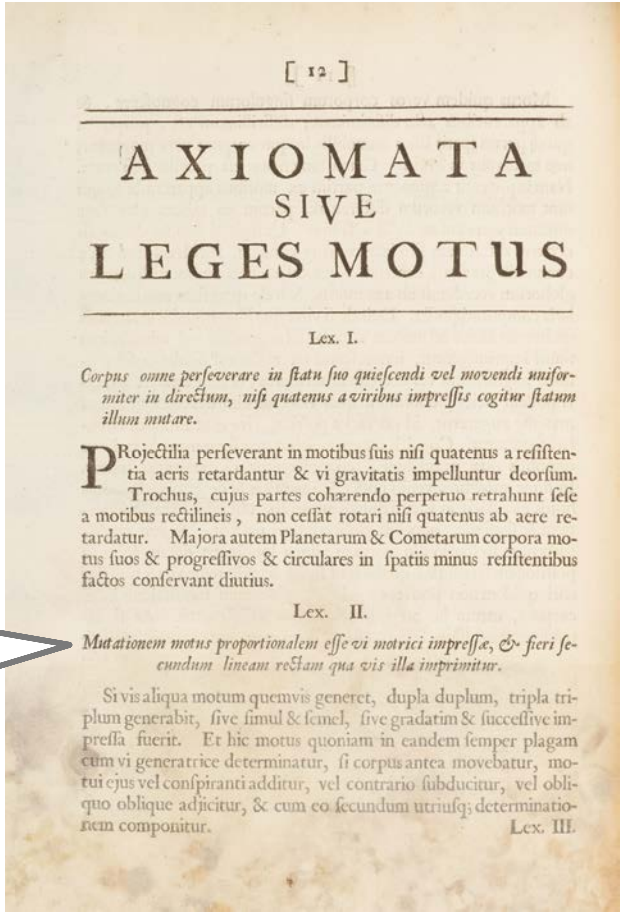
Bayesian Networks

Key Properties of Bayesian Networks

- Bayesian networks can encode causal direction, algebra cannot.
- Example: Newton’s Second Law of Motion

“Mutationem motus proportionalem esse vi motrici impressæ, & fieri secundum lineam rectam qua vis illa imprimitur.”

“A change in motion is proportional to the motive force impressed and takes place along the straight line in which that force is impressed.”


[12]

AXIOMATA
SIVE
LEGES MOTUS

Lex. I.

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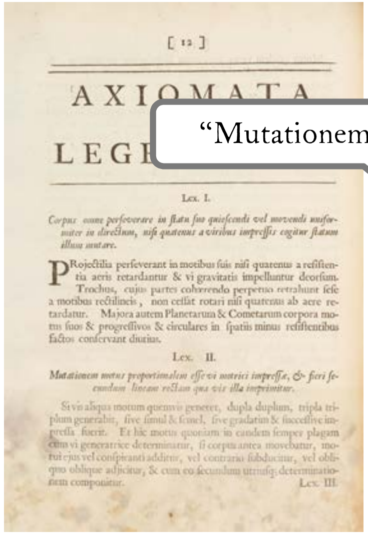
Lex. III.

The New Paradigm: Bayesian Networks

Limitations of Algebra: Newton’s Second Law of Motion



“Mutationem motus”

“vi motrici impressæ”

$$a = \frac{F}{m}$$

Causal Assignment

solving for *mass*

$$m = \frac{F}{a}$$

Causal Interpretation
Not Possible

The New Paradigm: Bayesian Networks

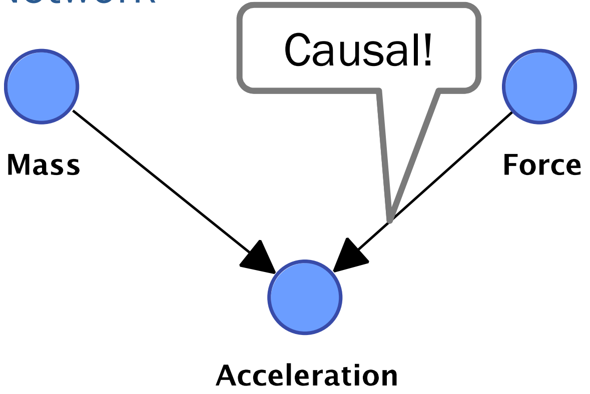
Key Properties of Bayesian Networks

- Bayesian networks can formally encode a causal direction*, algebra cannot.

Algebra vs. Bayesian Network

Causal or non-causal?

$$a = \frac{F}{m}$$



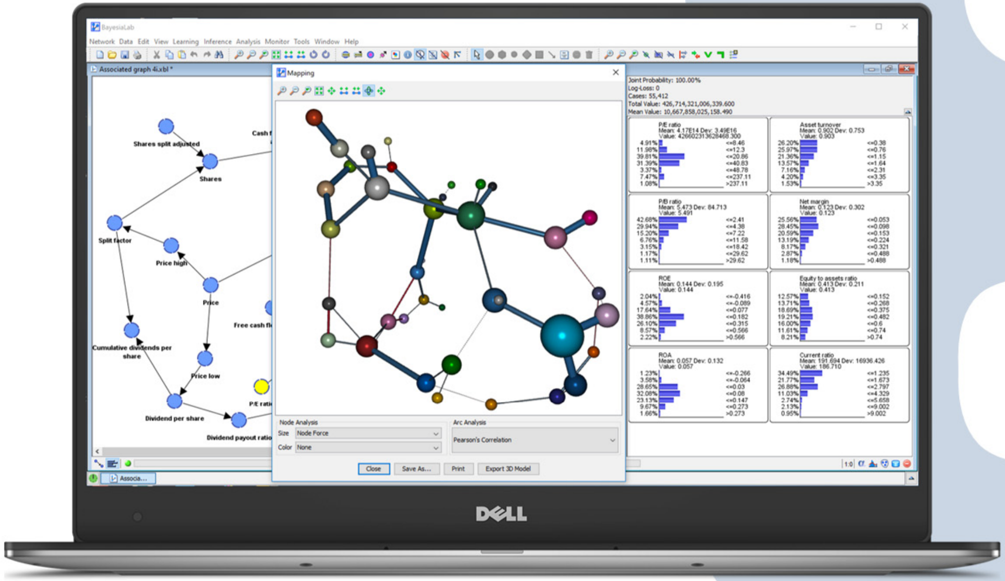
*Applies to manually encoded networks

Introducing BayesiaLab

Bayesian Networks for Research, Analytics, and Reasoning

Mathematical Formalism ➔ Research Software

BAYESIALAB



A desktop software for:

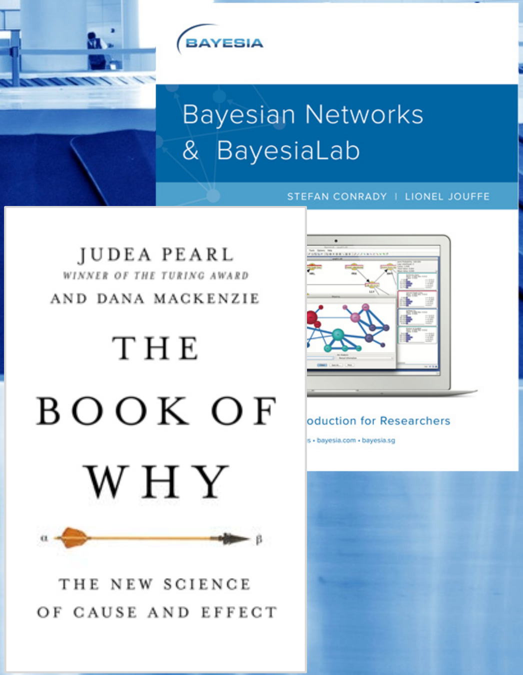
- encoding
- learning
- editing
- performing inference
- analyzing
- simulating
- optimizing

with Bayesian networks.

Constructing a Model Without Data!

Introductory Example

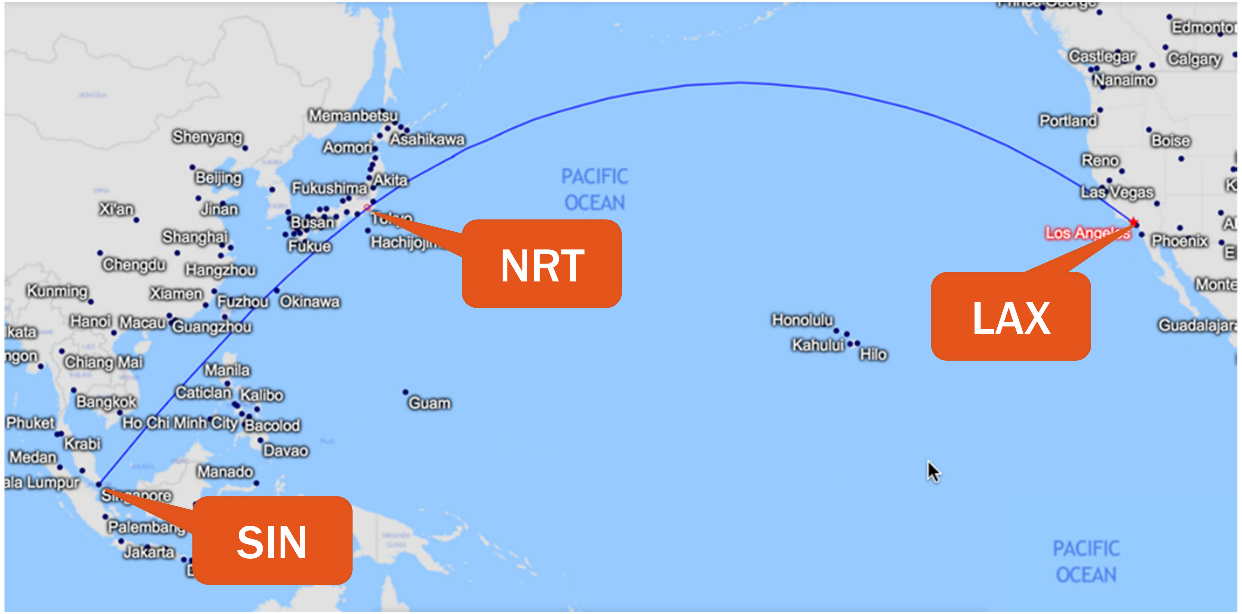
Where is my bag?



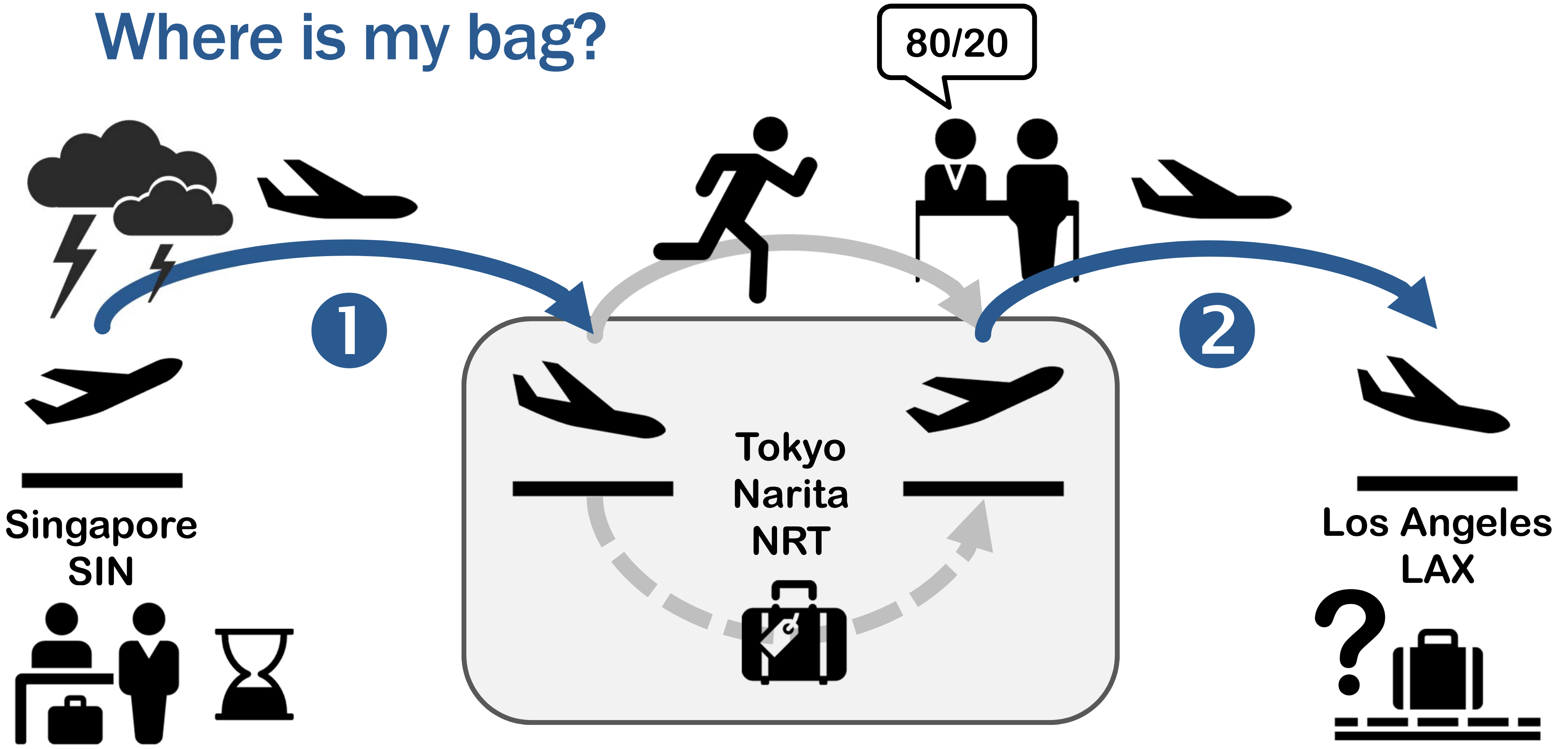
Knowledge Modeling & Reasoning Under Uncertainty

Where is my bag?

Travel Route: Singapore (SIN) ➔ Tokyo/Narita (NRT) ➔ Los Angeles (LAX)



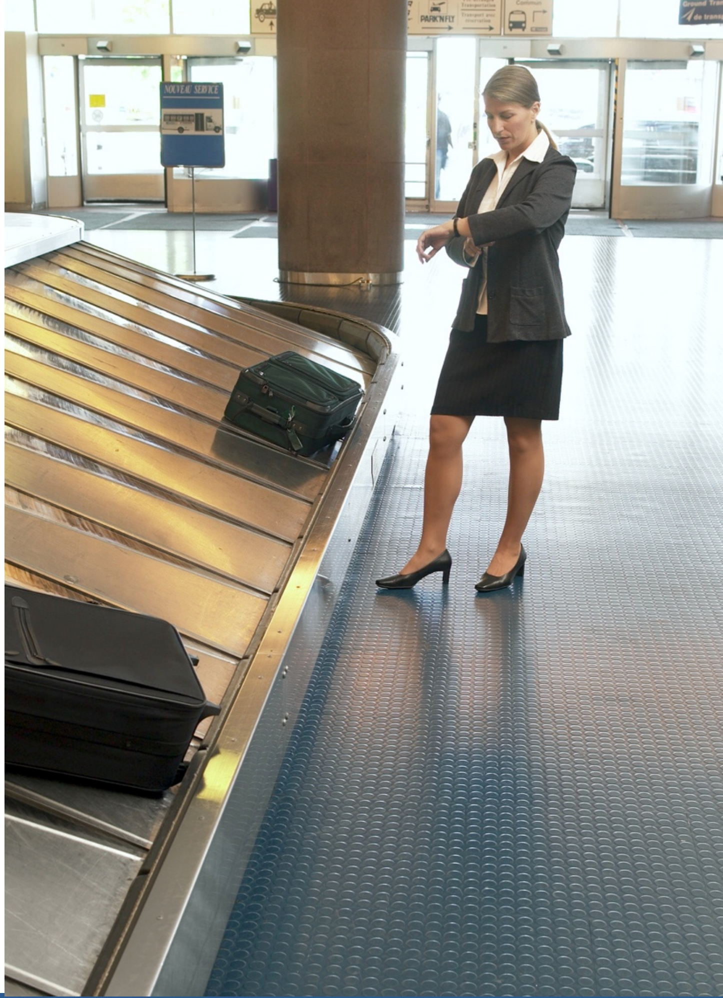
Where is my bag?



Where is my bag?

Scenario

- Luggage delivery starts onto the carousel.
- **After 5 minutes**, I still do not see my bag.
- What is the probability that I will still get my bag?

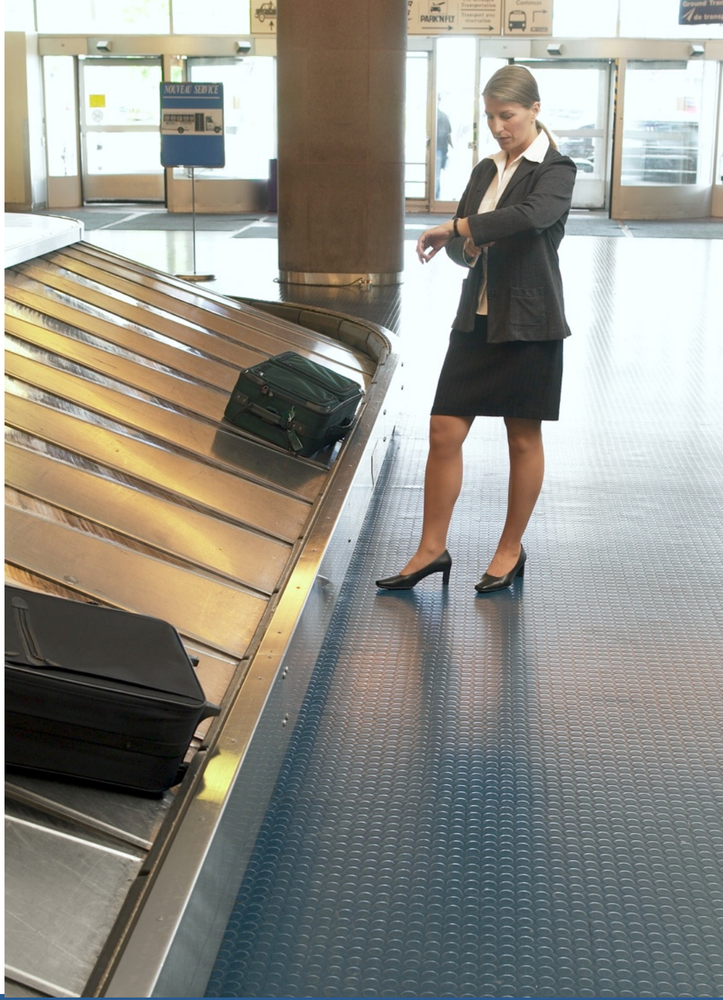


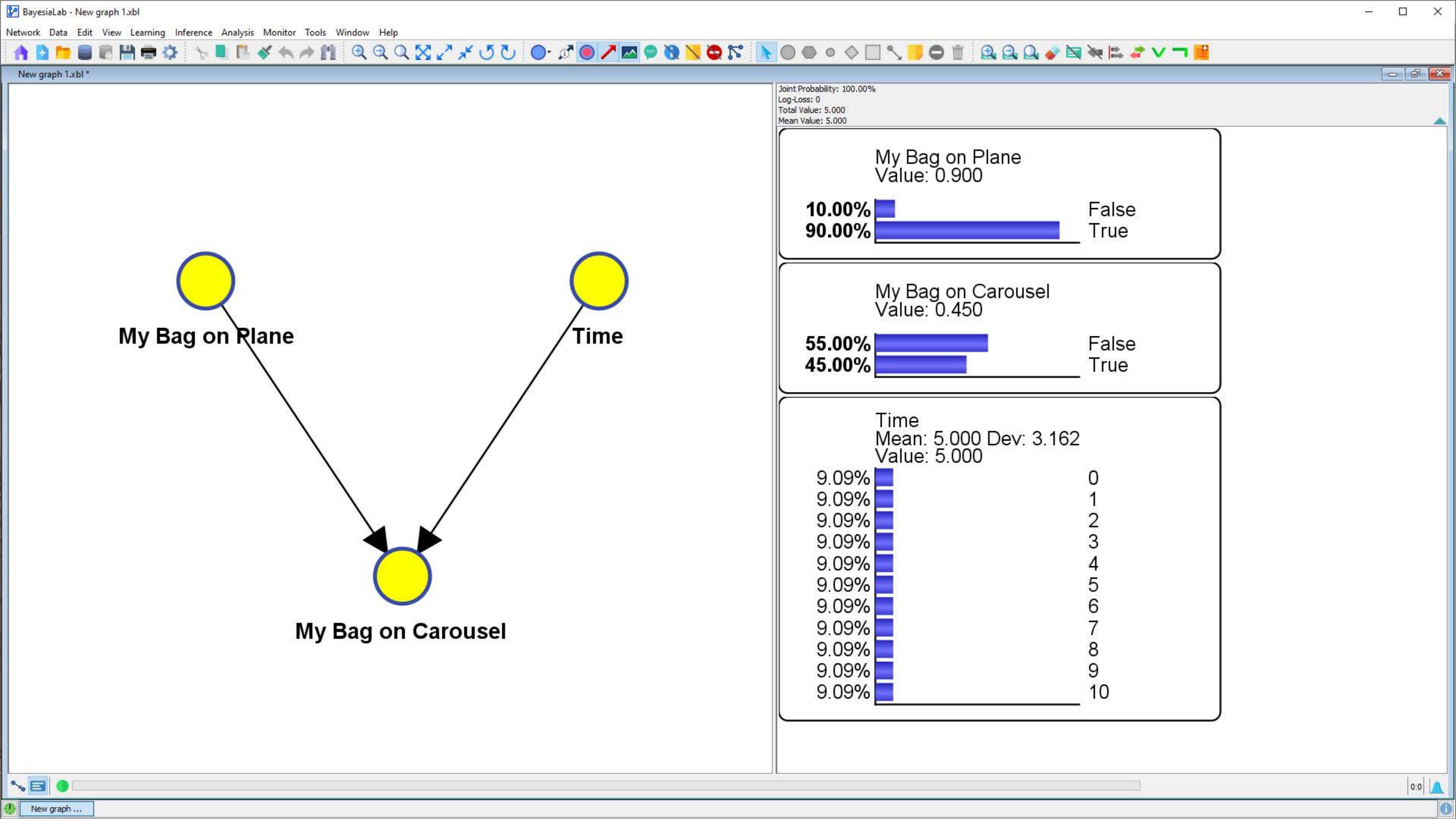

SINGAPORE AIRLINES
152
154
156
D-ABYJ
Sky Chefs
IS MY BAG IN THERE?

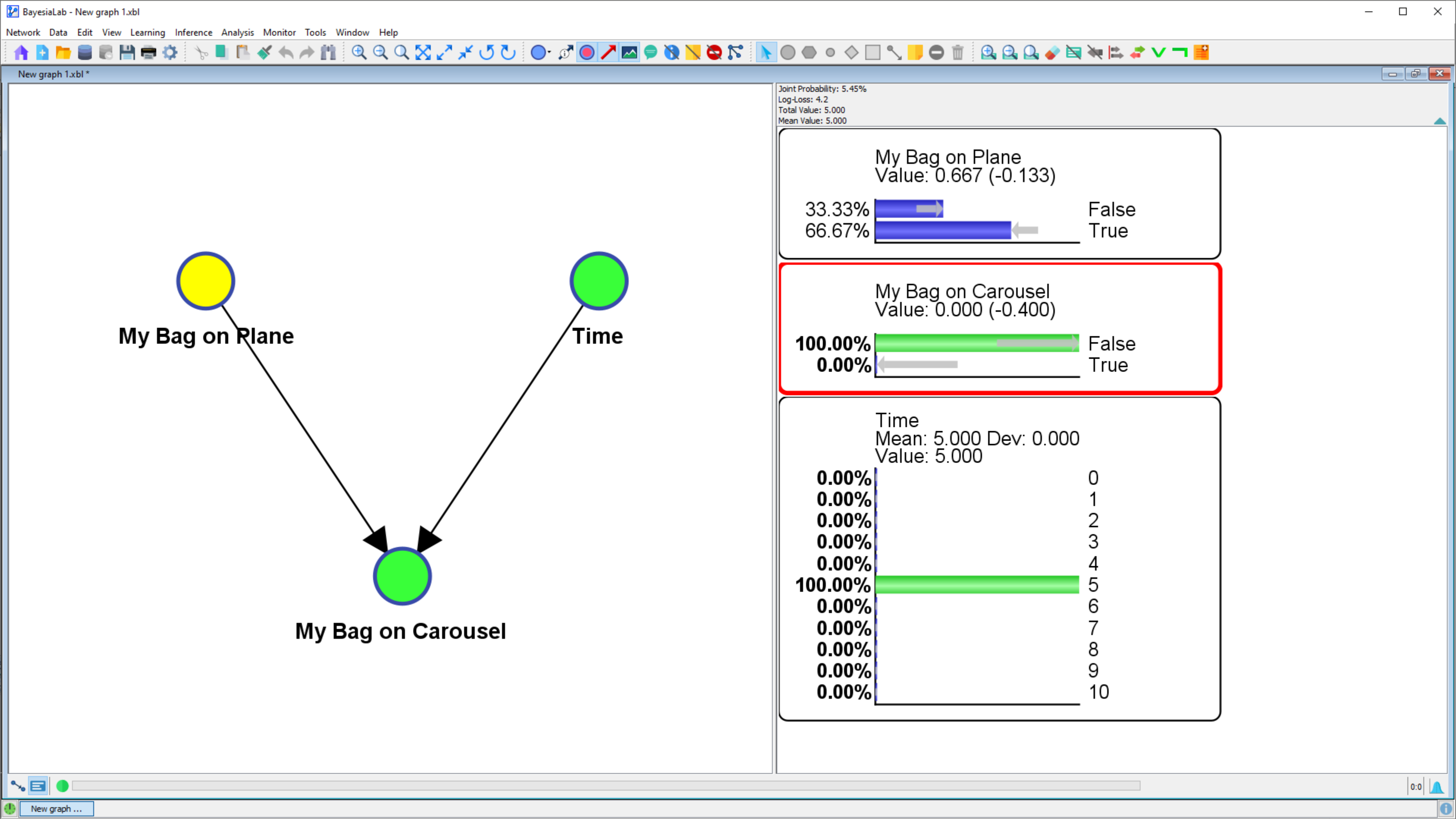
Where is my bag?

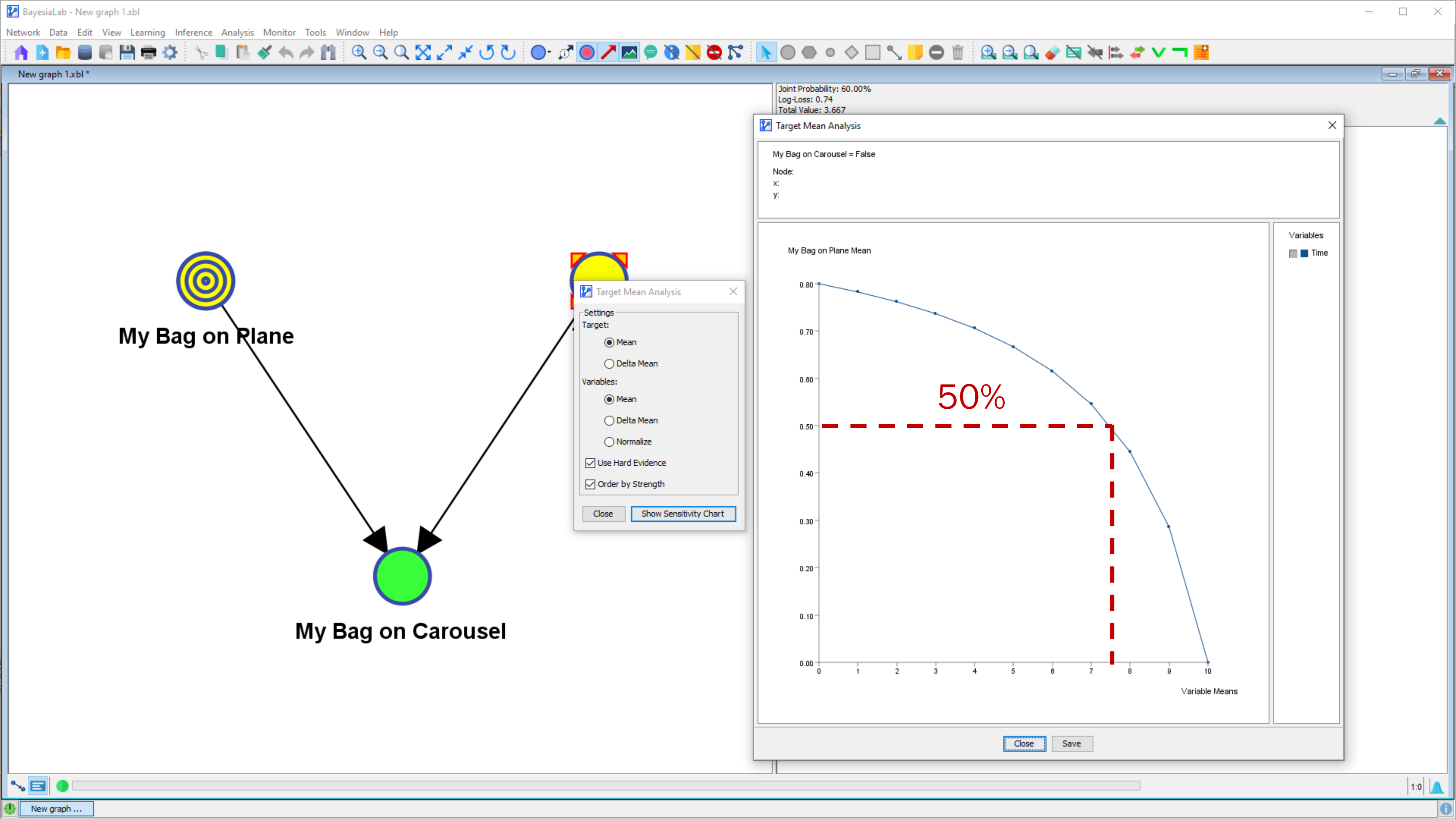
Proposed Workflow

- Encode the available — albeit very limited — knowledge into a Bayesian network.
- Use BayesiaLab to perform probabilistic inference given our observations.




BayesiaLab - New graph 1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 1.xbl *
My Bag on Plane
Time
My Bag on Carousel
Joint Probability: 100.00%
Log-Loss: 0
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
Value: 0.900
10.00% False
90.00% True
My Bag on Carousel
Value: 0.450
55.00% False
45.00% True
Time
Mean: 5.000 Dev: 3.162
Value: 5.000
9.09% 0
9.09% 1
9.09% 2
9.09% 3
9.09% 4
9.09% 5
9.09% 6
9.09% 7
9.09% 8
9.09% 9
9.09% 10
New graph ...


BayesiaLab - New graph 1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 1.xbl *
Joint Probability: 5.45%
Log-Loss: 4.2
Total Value: 5.000
Mean Value: 5.000
My Bag on Plane
Time
My Bag on Carousel
My Bag on Plane
Value: 0.667 (-0.133)
33.33% False
66.67% True
My Bag on Carousel
Value: 0.000 (-0.400)
100.00% False
0.00% True
Time
Mean: 5.000 Dev: 0.000
Value: 5.000
0.00% 0
0.00% 1
0.00% 2
0.00% 3
0.00% 4
100.00% 5
0.00% 6
0.00% 7
0.00% 8
0.00% 9
0.00% 10
New graph ...


BayesiaLab - New graph 1.xbl
Network Data Edit View Learning Inference Analysis Monitor Tools Window Help
New graph 1.xbl *
Joint Probability: 60.00%
Log-Loss: 0.74
Total Value: 3.667
My Bag on Plane
My Bag on Carousel
Target Mean Analysis
Settings
Target:
Mean
Delta Mean
Variables:
Mean
Delta Mean
Normalize
Use Hard Evidence
Order by Strength
Close
Show Sensitivity Chart
Target Mean Analysis
My Bag on Carousel = False
Node:
x:
y:
My Bag on Plane Mean
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0 1 2 3 4 5 6 7 8 9 10
50%
Variable Means
Variables
Time
Close
Save
New graph ...

Coffee Break

CASE STUDY

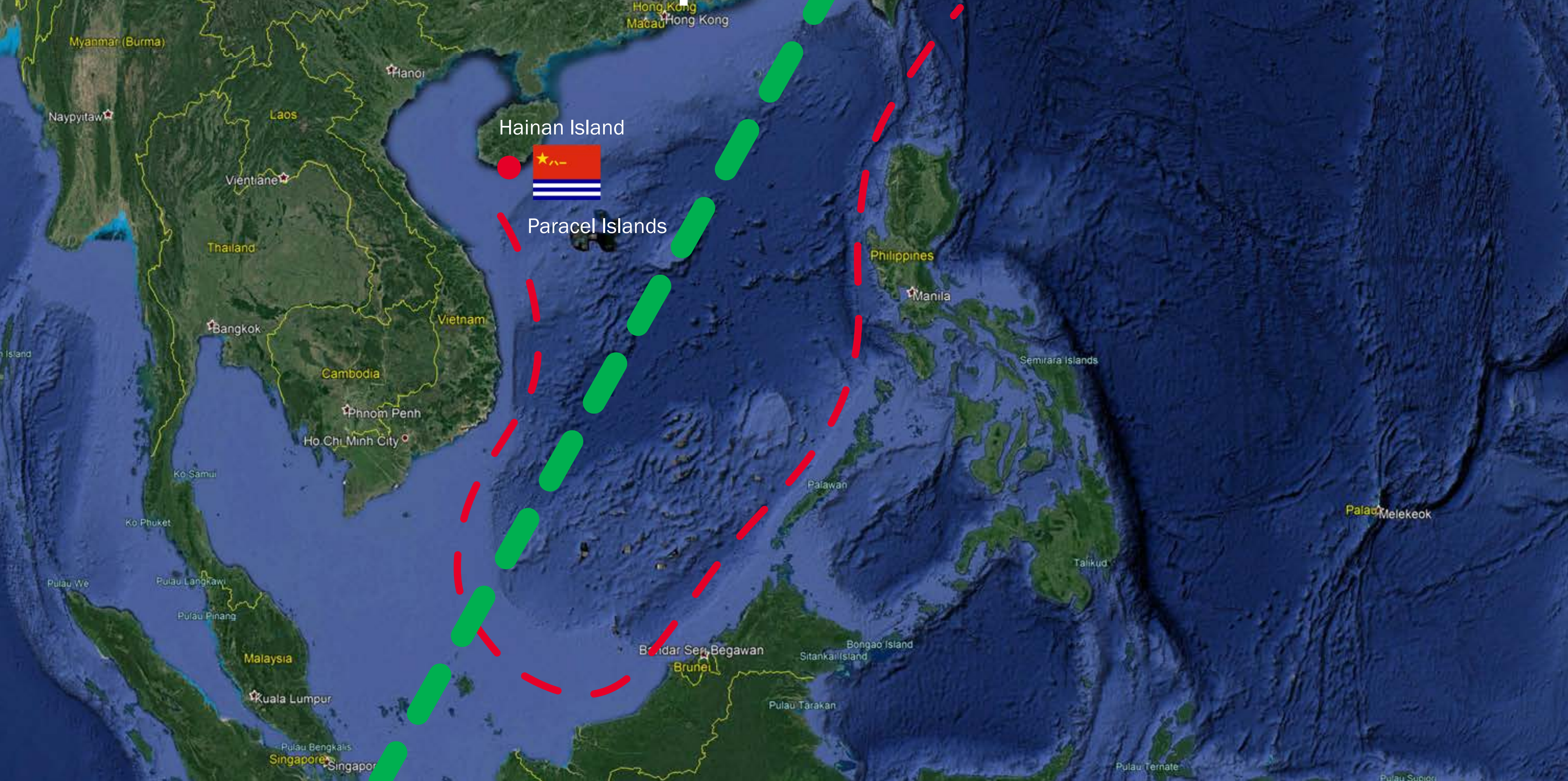
BACKGROUND AND CONTEXT

Caveat

Geopolitical Reasoning

- Any references to potential adversaries, enemies, conflicts, hostilities, etc., are strictly for methodological illustration purposes.
- We are not expressing any opinions about the legitimacy of territorial claims in the South China Sea.
- All background information provided in this seminar is from publicly available sources.
- All numerical values shows are purely fictional.
- The problem domain is highly simplified for illustration purposes.

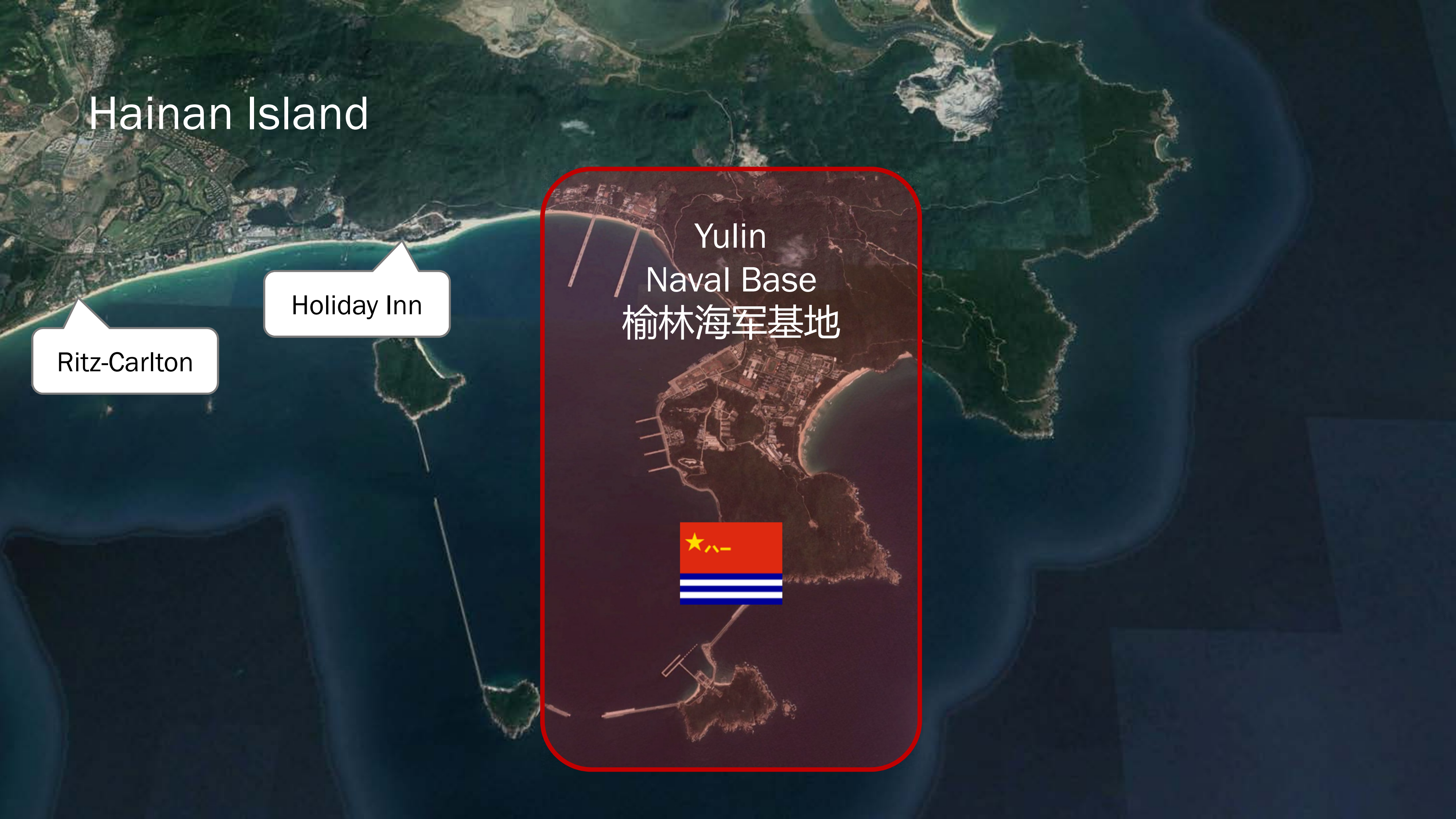
South China Sea Dispute




Hainan Island
Yulin
Naval Base
榆林海军基地
八一


Hainan Island
Yulin
Naval Base
榆林海军基地
八一


Jin-Class (Type 094) SSBN

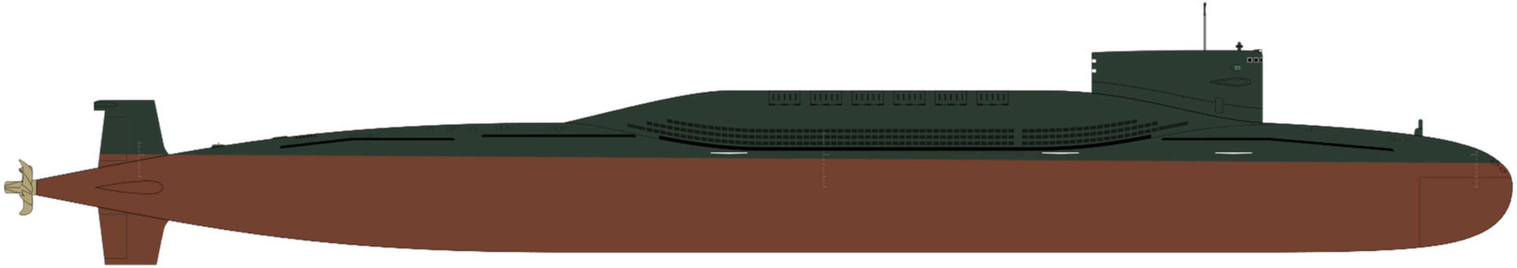

Hainan Island
Holiday Inn
Ritz-Carlton
Yulin
Naval Base
榆林海军基地


South China Sea

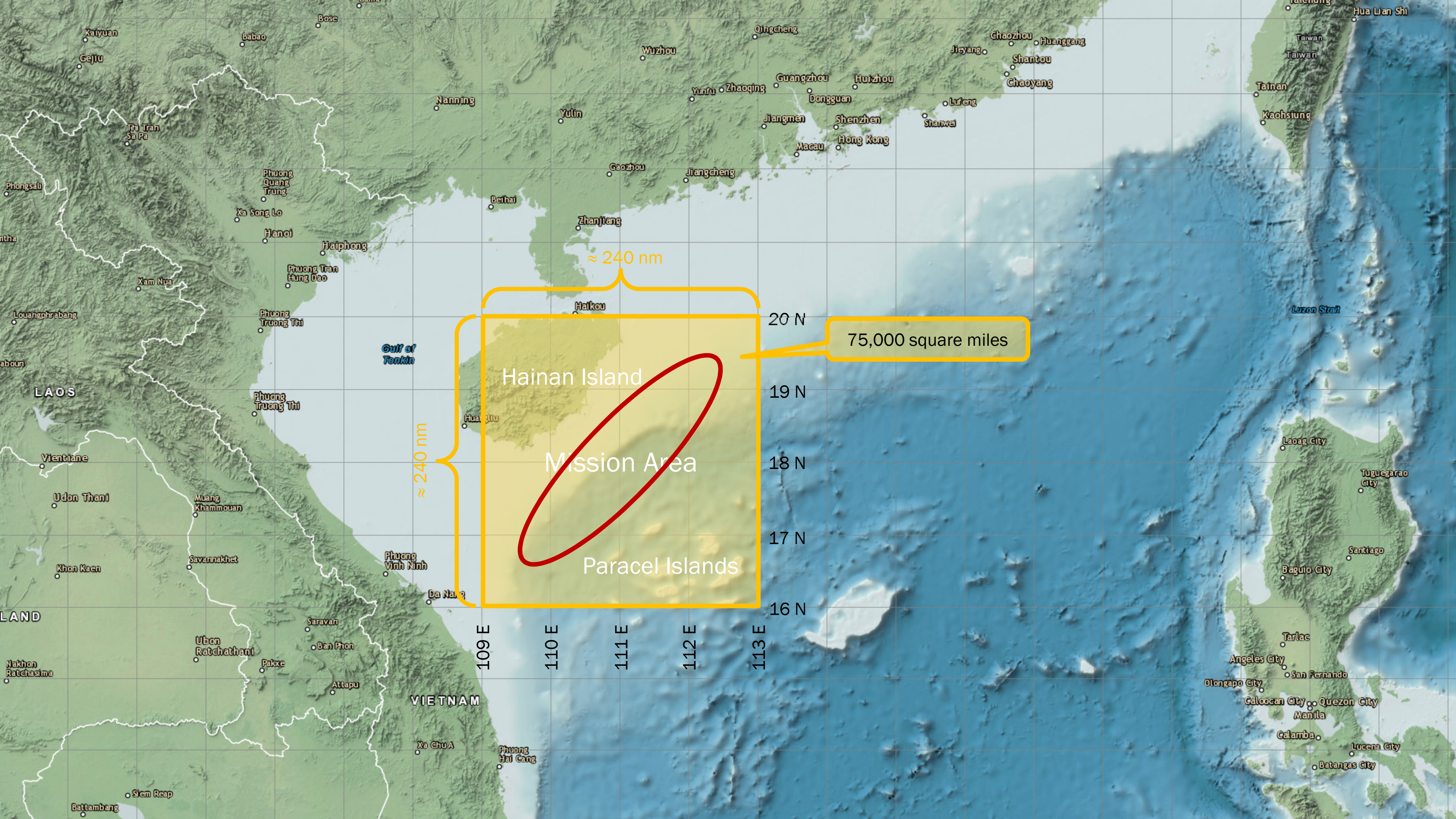
Scenario

Fictional Mission

- An American Virginia-class (SSN 774 class) nuclear-powered attack submarine is on patrol to monitor the sea trials of a new Chinese Jin-class (Type 094) ballistic missile submarine (SSBN).
- The object of interest is based at Yulin (Sanya) Naval Base on Hainan Island.



Jin-Class (Type 094) SSBN



≈ 240 nm
≈ 240 nm
75,000 square miles
Hainan Island
Mission Area
Paracel Islands
20 N
19 N
18 N
17 N
16 N
109 E
110 E
111 E
112 E
113 E
Gulf of Tonkin
Luzon Strait
LAOS
VIETNAM
Haikou
Hanoi
Haiphong
Da Nang
Zhanjiang
Beihai
Nanning
Guangzhou
Shenzhen
Hong Kong
Macau
Kaohsiung
Tainan
Manila
Quezon City
Baguio City
Vientiane
Udon Thani

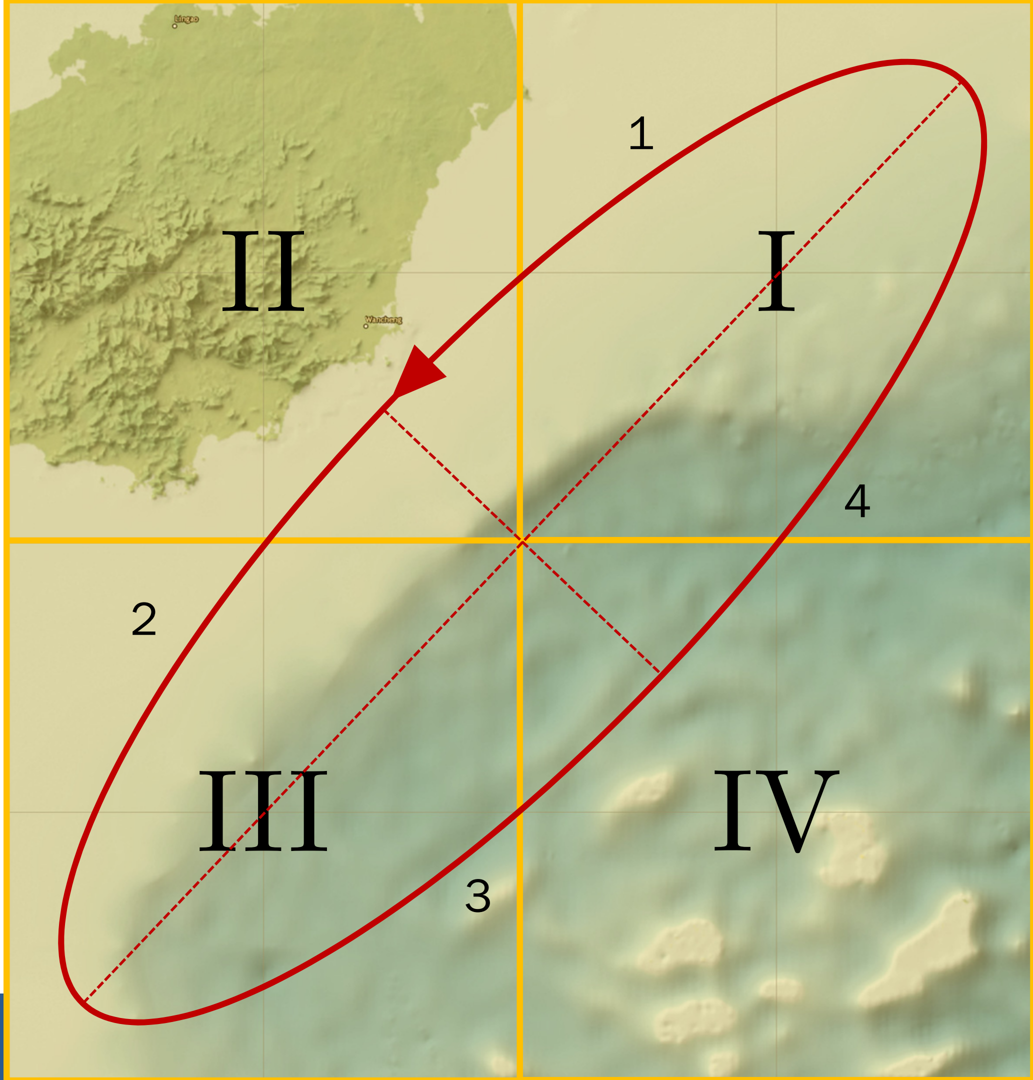
Scenario

Fictional Mission

- Planned duration: 4 days.
- No communication from submarine during mission to avoid detection.

Mission Area

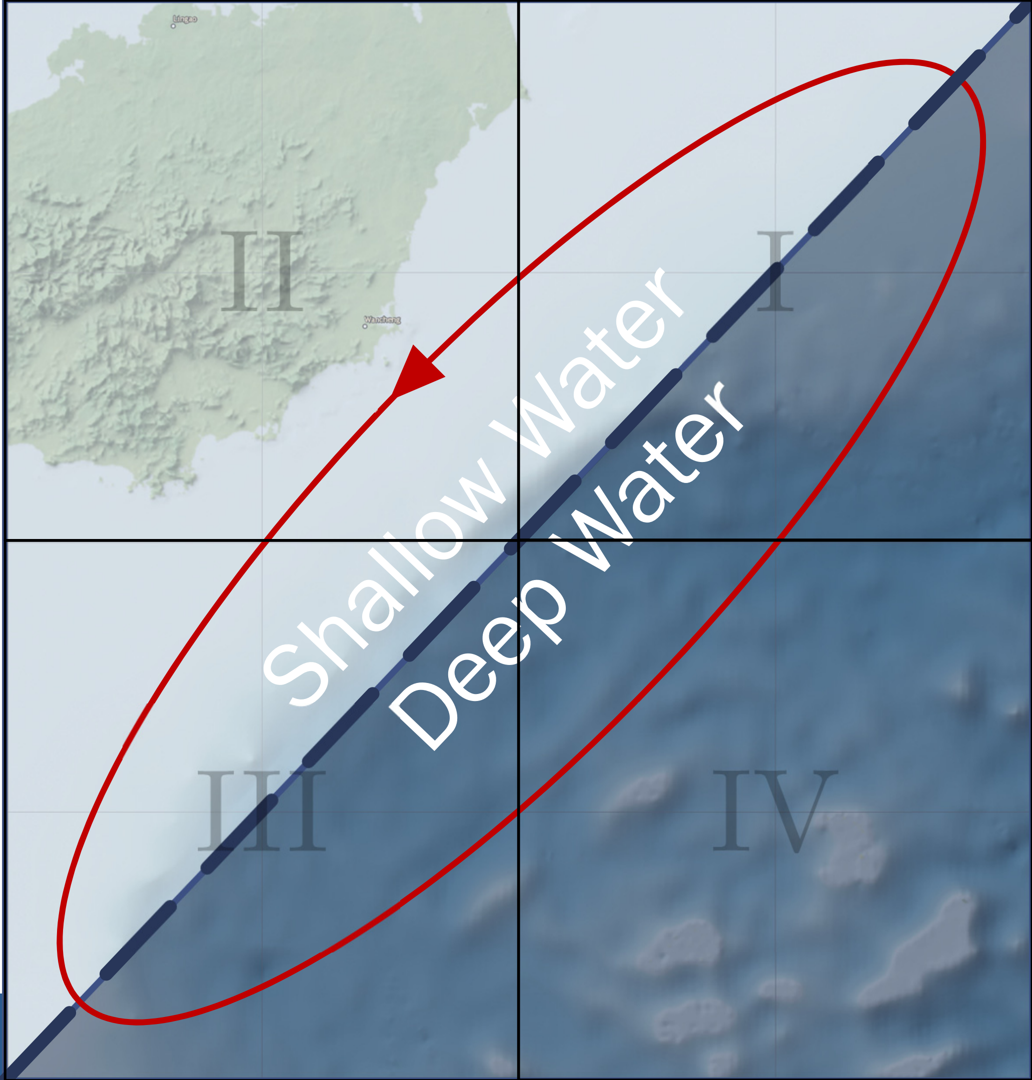
- Divided into four quadrants.
- Approximately oval route.
- Submarine can adjust course as per operational requirements.



Scenario

Mission Area Considerations

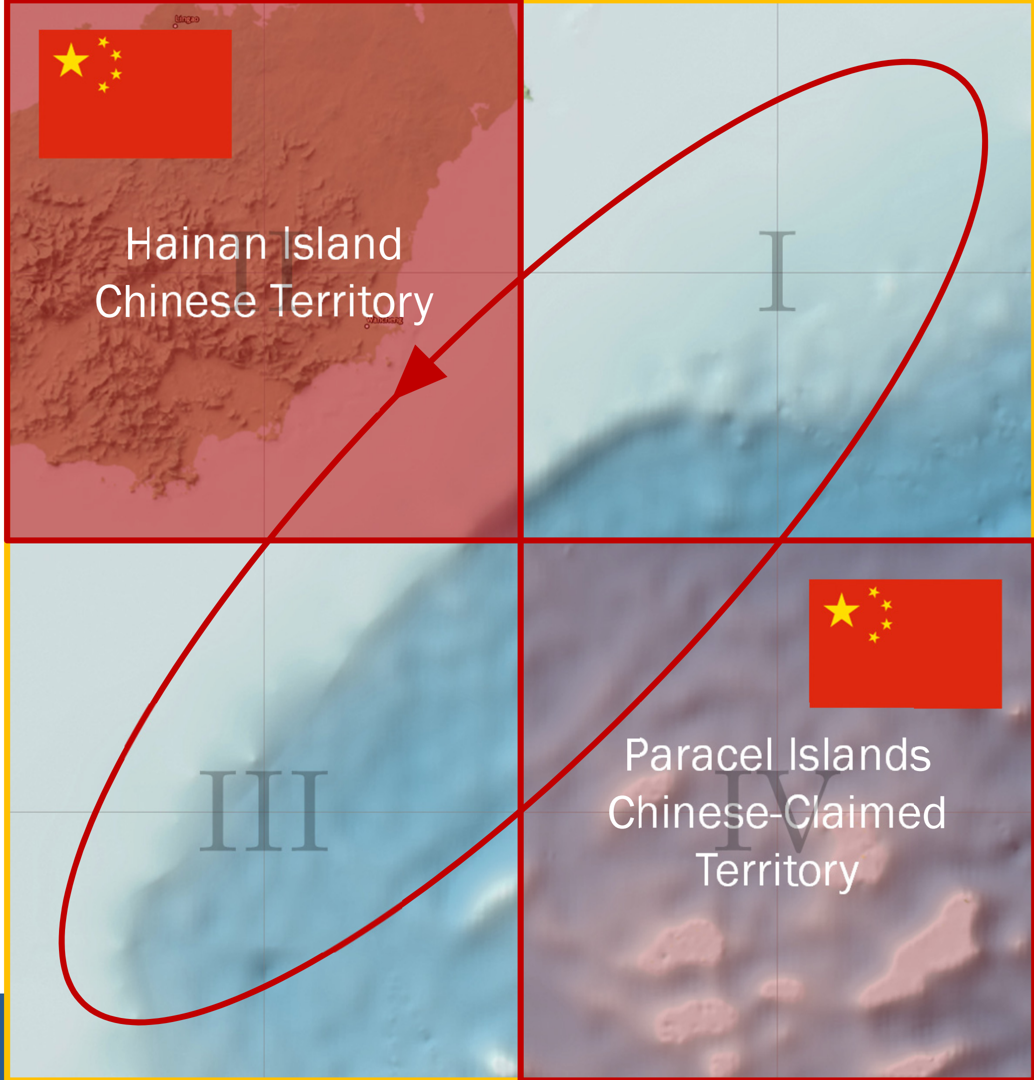
- South China Continental Shelf
    - Shallow, coastal waters (<100m)
    - Deep water (>1000m)



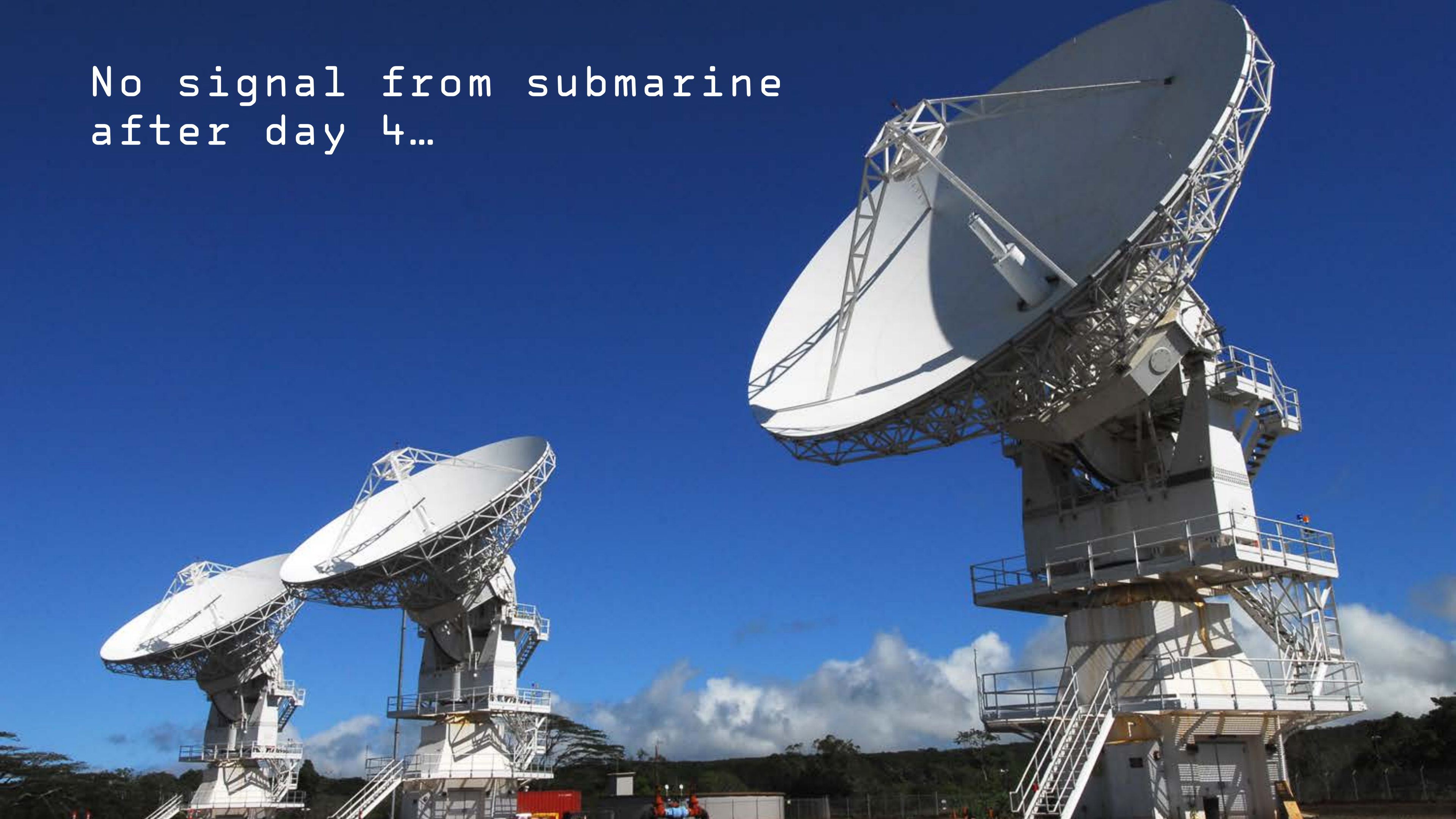
Scenario

Mission Area Considerations

- Hainan Island
  Chinese territorial waters
- Paracel Islands
  Chinese-*claimed* territorial waters




ON PATROL
SOUTH CHINA SEA


No signal from submarine
after day 4…

Missing Submarine

- Where is the submarine?
- What happened?
- What are the consequences of detection?
    - Capture?
    - Hostile military action?
- What are the risks of a search effort?
- Where should the search start?
- What are the chances of a successful rescue?
- For how long can the crew survive?
- What are the political implications?

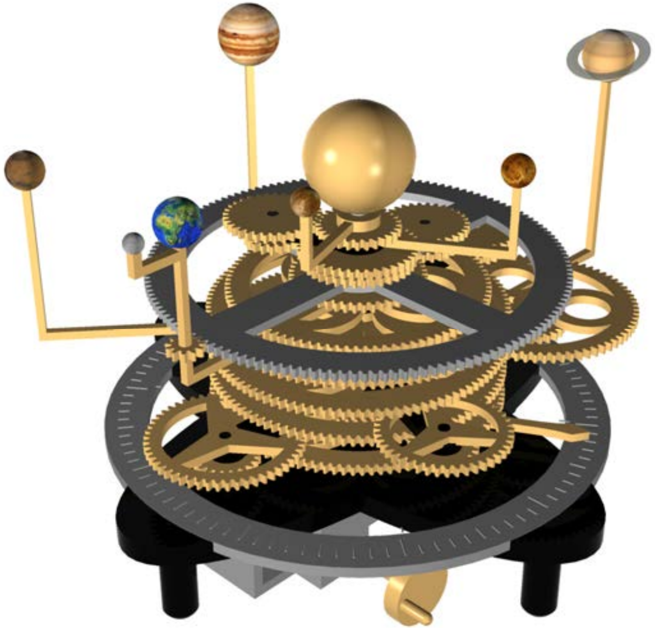
Undersea Rescue?

Should a search and rescue effort be launched?

Constructing a Model for Decision Support

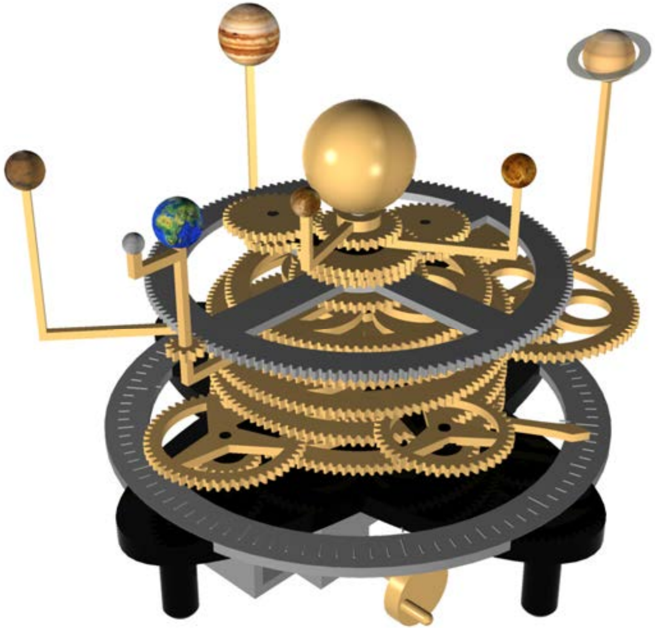
Constructing a Model for Decision Support

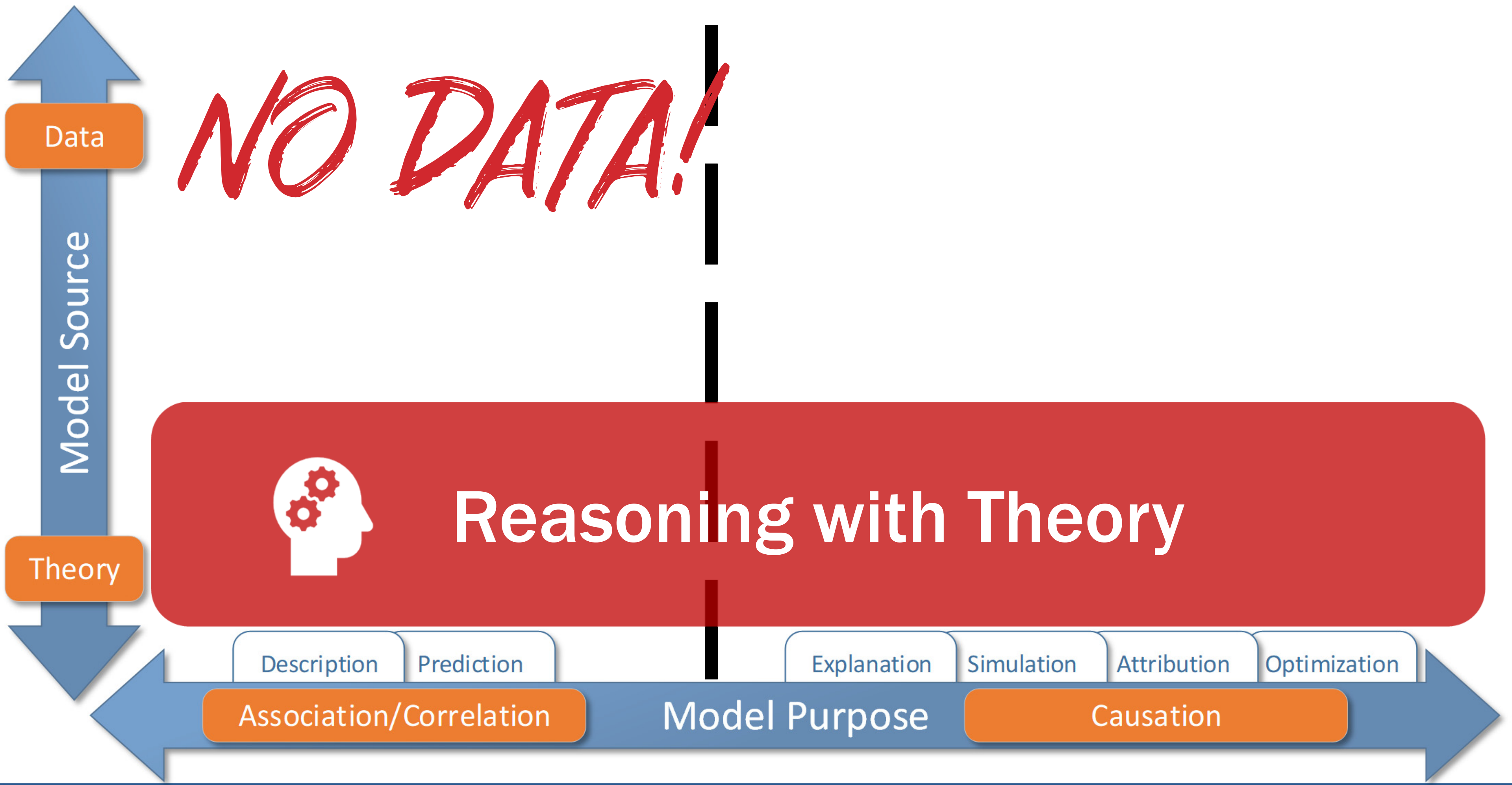
A model that can help us understand, think, reason, predict, and simulate.



Constructing a Model for Decision Support

A model that can help us understand, think, reason, predict, and simulate.

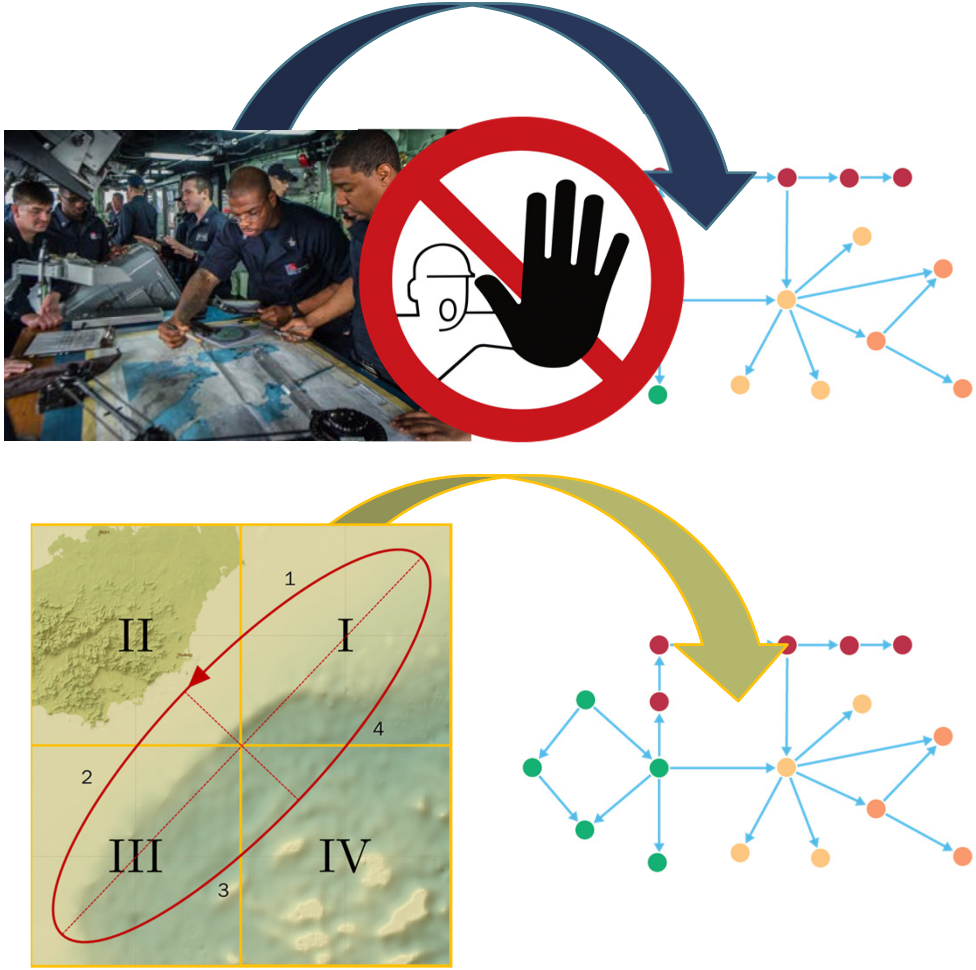



NO DATA!
Data
Model Source
Theory
Reasoning with Theory
Description
Prediction
Explanation
Simulation
Attribution
Optimization
Association/Correlation
Model Purpose
Causation

Constructing a Model

Key Considerations

- We need to encode how the "world works," not how we reason.
- I.e., we are not building a decision tree!



Constructing a Model for Decision Support

Proposed Approach for Decision Making

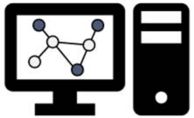
1. Domain Knowledge Encoding

2. Probability Elicitation

Position (Quadrant)	<500m	>500m
1	50.000	50.000
2	90.000	10.000
3	50.000	50.000
4	10.000	90.000

3. Cost/Utility Assessment

4. Inference & Optimization



Constructing a Model for Decision Support

Proposed Approach for Decision Making

1. Domain Knowledge Encoding

2. Probability Elicitation

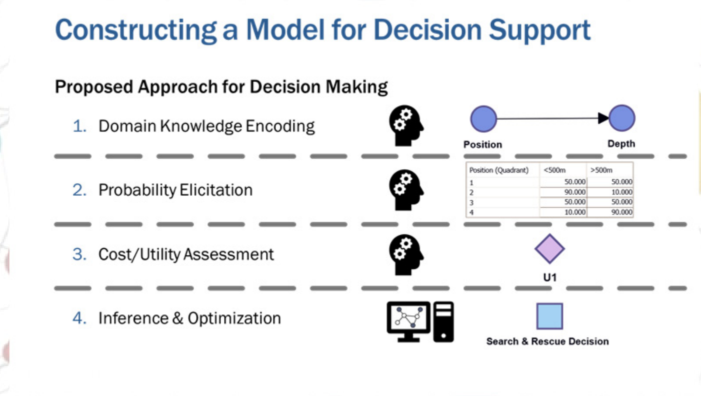
Position (Quadrant)	<500m	>500m
1	50.000	50.000
2	90.000	10.000
3	[illegible]	[illegible]
4	10.000	90.000

Bayesia Expert Knowledge Elicitation Environment

BEKEE

3. Cost/Utility Assessment

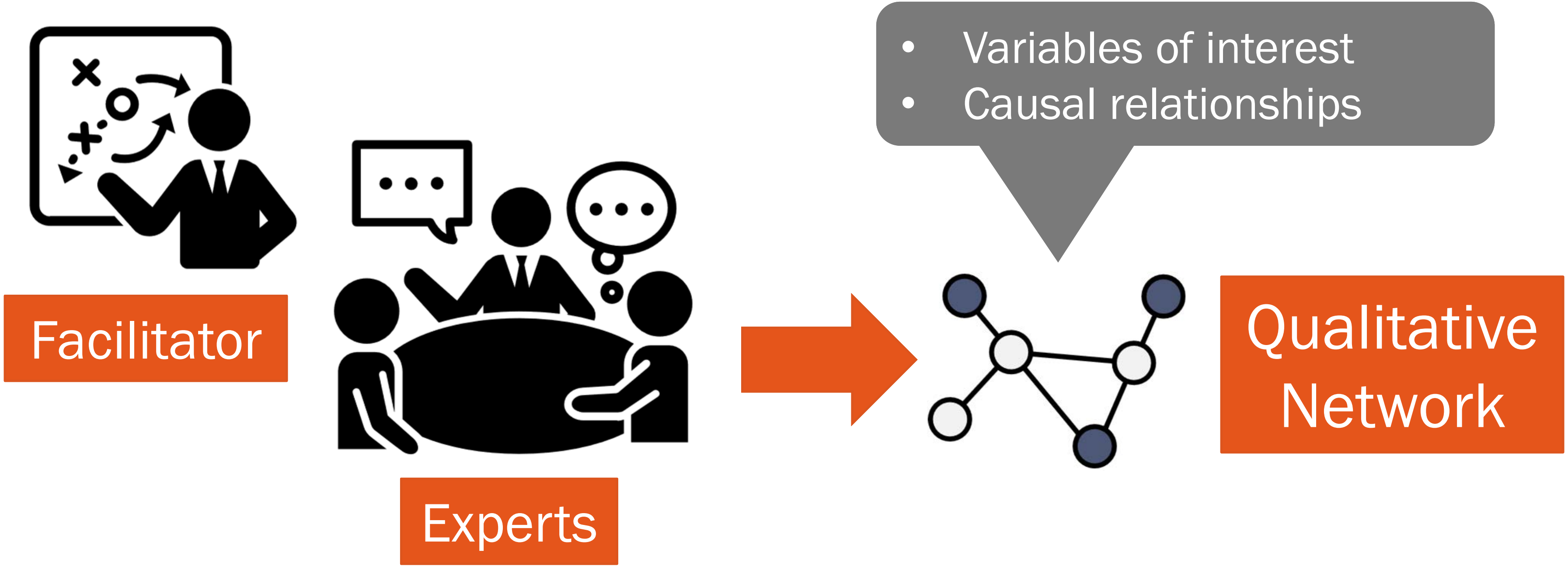
4. Inference & Optimization



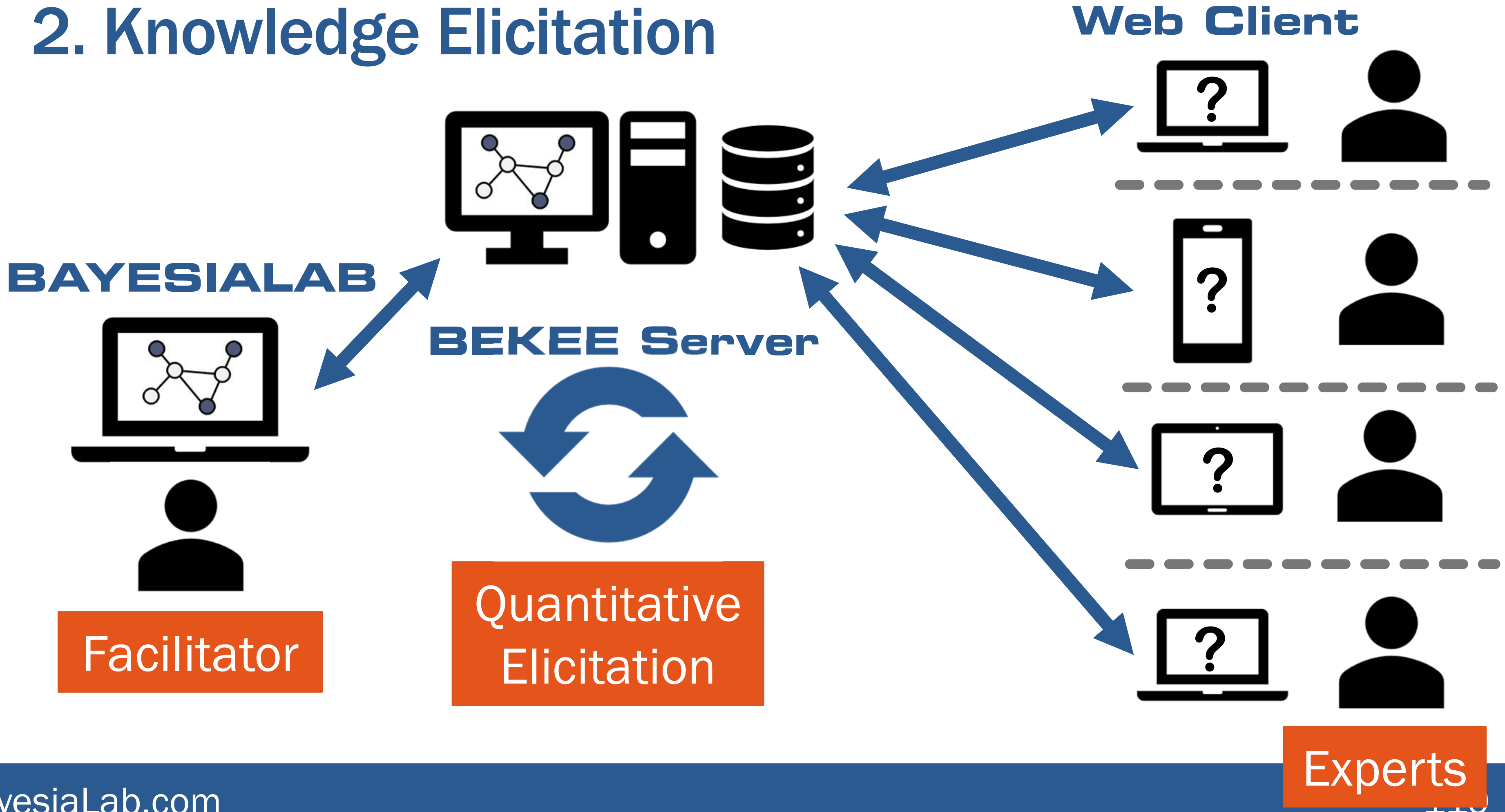
Workflow Details

Constructing a Model for Decision Support

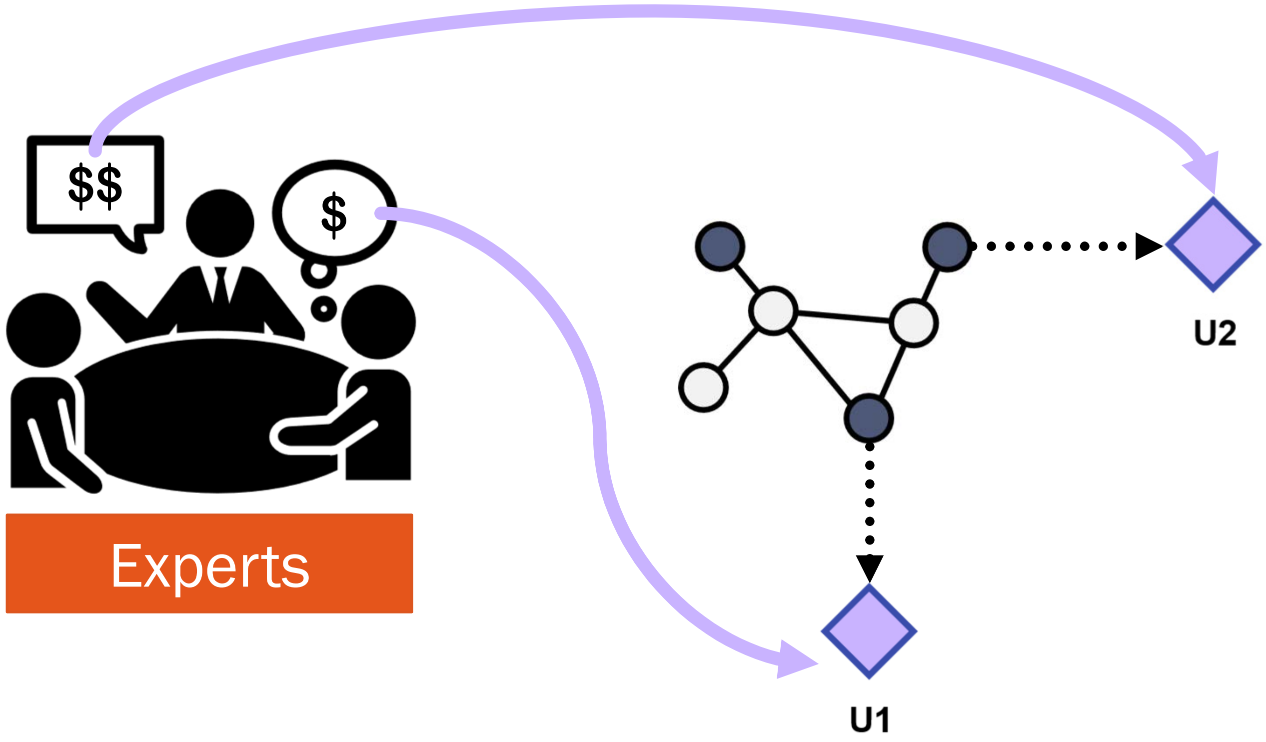
1. Brainstorming & Model Construction



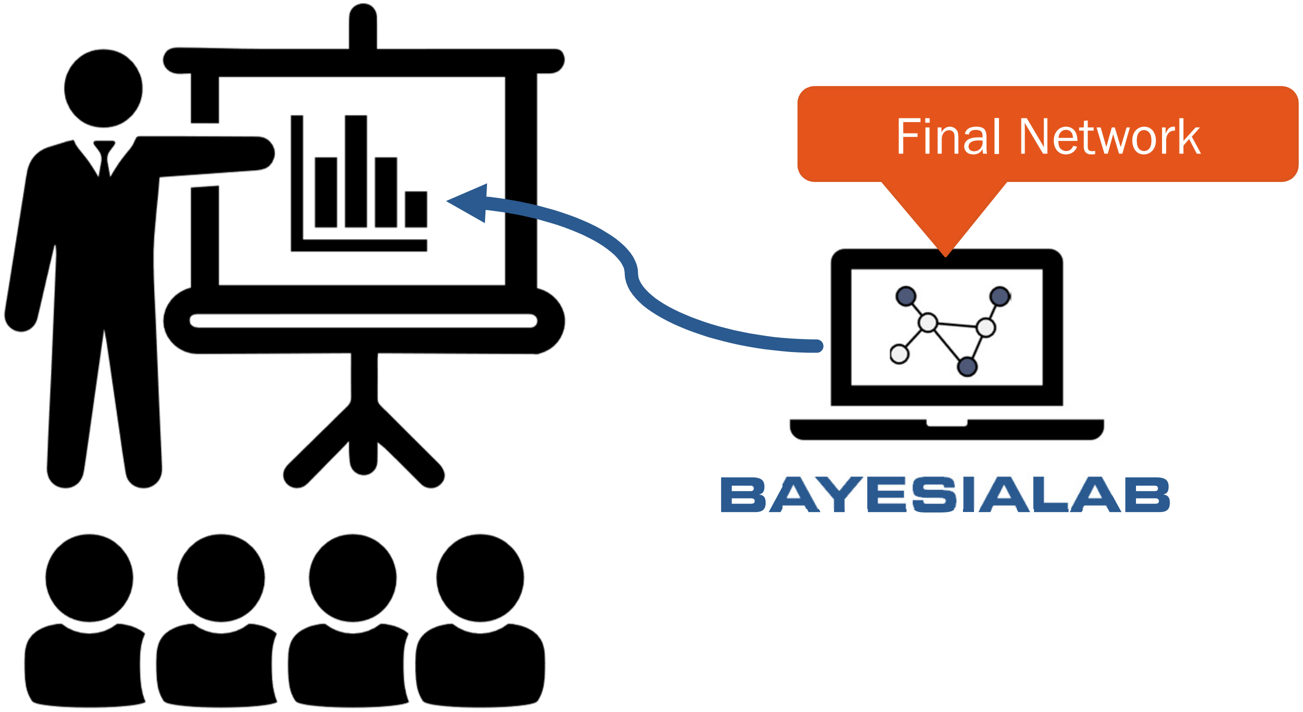
2. Knowledge Elicitation

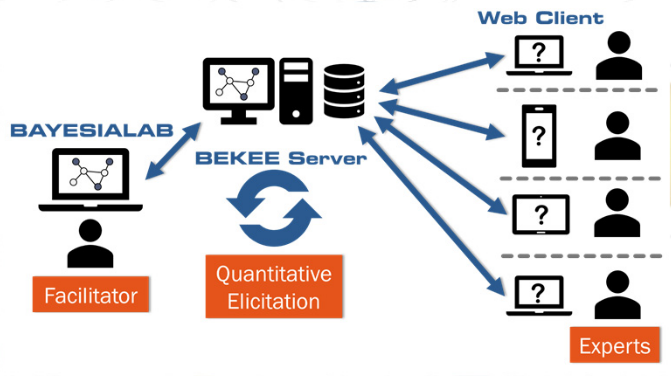


3. Assignment of Cost, Values, and Utilities



4. Inference, Analysis, and Decision Optimization





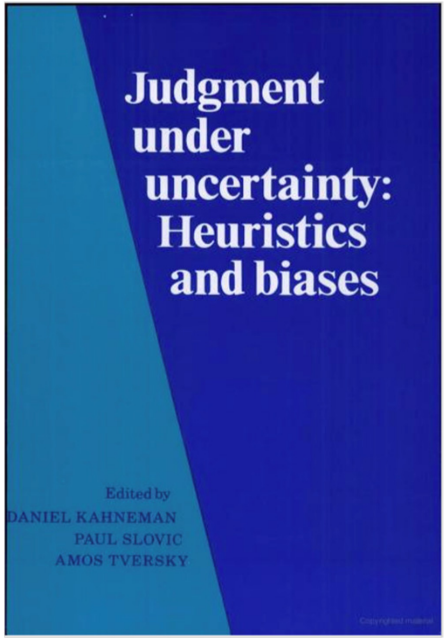
Details on Knowledge Elicitation

Introducing the Delphi Method and the Bayesia Expert Knowledge Elicitation Environment (BEKEE)

Motivation: Individual Biases

Examples

- Overconfidence
- Confirmation bias
- Framing effect
- Escalation of commitment
- Availability bias
- Illusion of control
- Anchoring bias



Motivation: Group Biases

Examples

- Groupthink (“toeing the line”)
- Social loafing (“hiding in the crowd”)
- Group polarization (“taken to the extreme”)
- Escalation of commitment (“throwing good money after bad”, “sunken costs fallacy”)

The Delphi Method

Interacting Groups

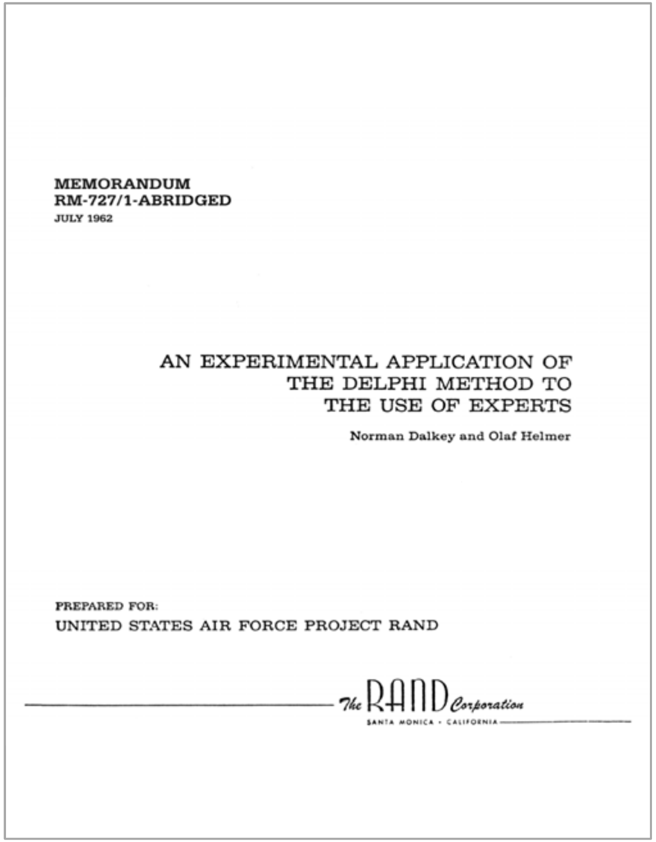
- Take the positive, e.g.
    - Knowledge from a variety of sources
    - Creative synthesis
- Prevent the negative, e.g.
    - Groupthink ("toeing the line")
    - Social loafing ("hiding in the crowd")
    - Group polarization ("taken to the extreme")

A CONSULTATION OF THE DELPHIC ORACLE:
THEMIS ON THE TRIPOD WITH KING AEGEUS,
C. 440 BC

The Delphi Method

Origins

- The original Delphi method was developed in the 1940s and 50s by Norman Dalkey of the RAND Corporation.
- The Delphi method was devised in order to obtain the most **reliable opinion consensus of a group of experts** by subjecting them to a series of questionnaires in depth interspersed with controlled opinion feedback.


MEMORANDUM
RM-727/1-ABRIDGED
JULY 1962

AN EXPERIMENTAL APPLICATION OF
THE DELPHI METHOD TO
THE USE OF EXPERTS

Norman Dalkey and Olaf Helmer

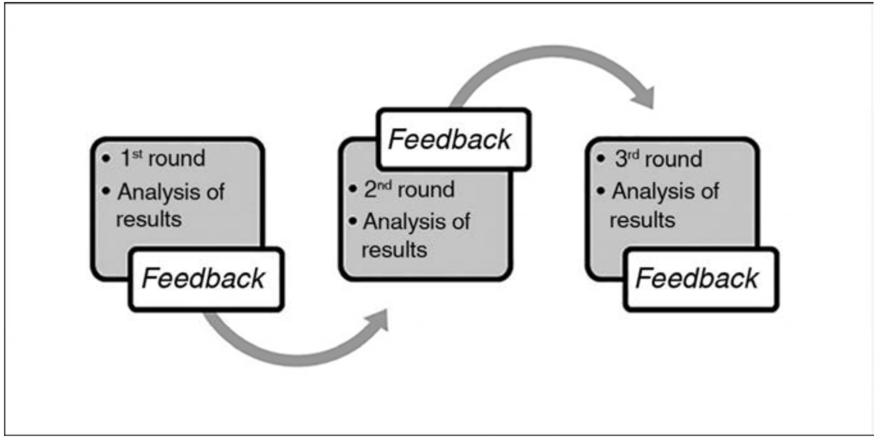
PREPARED FOR:
UNITED STATES AIR FORCE PROJECT RAND

The RAND Corporation
SANTA MONICA • CALIFORNIA

The Delphi Method

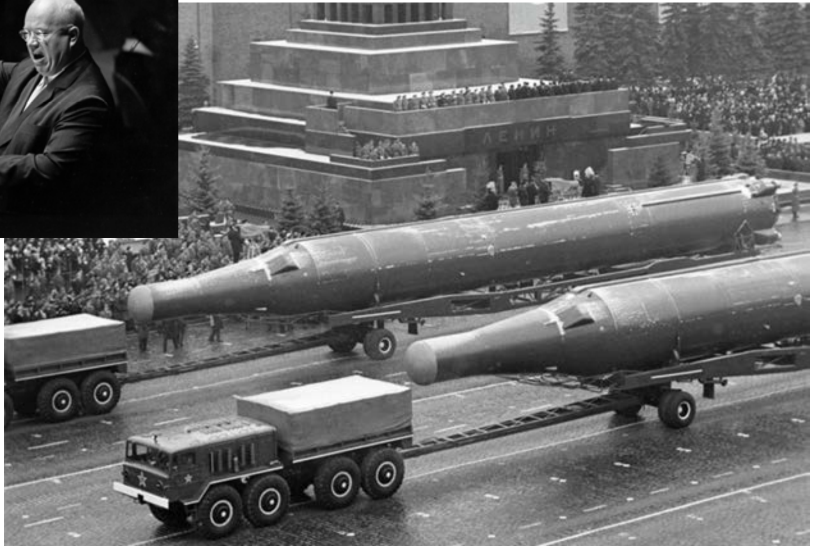
The Classical Delphi

- Interviews via questionnaires
- Anonymity of participants
- Iteration
- Controlled feedback
- Statistical aggregation



First Experimental Application

"to solicit expert opinion to the selection, from the point of view of a Soviet strategic planner, of an optimal U.S. industrial target system..."



Delphi Method Assessment

"In view of the absence of a proper theoretical foundation and the consequent inevitability of having, to some extent, to rely on intuitive expertise—a situation which is still further compounded by its multidisciplinary characteristics—we are faced with two options: **we can either throw up our hands in despair** and wait until we have an adequate theory enabling us to deal with socioeconomic and political problems as confidently as we do with problems in physics and chemistry, **or we can make the most of an admittedly unsatisfactory situation and try to obtain the relevant intuitive insights of experts** and then use their judgments as systematically as possible."

ANALYSIS OF THE FUTURE: THE DELPHI METHOD

Olaf Helmer

March 1967

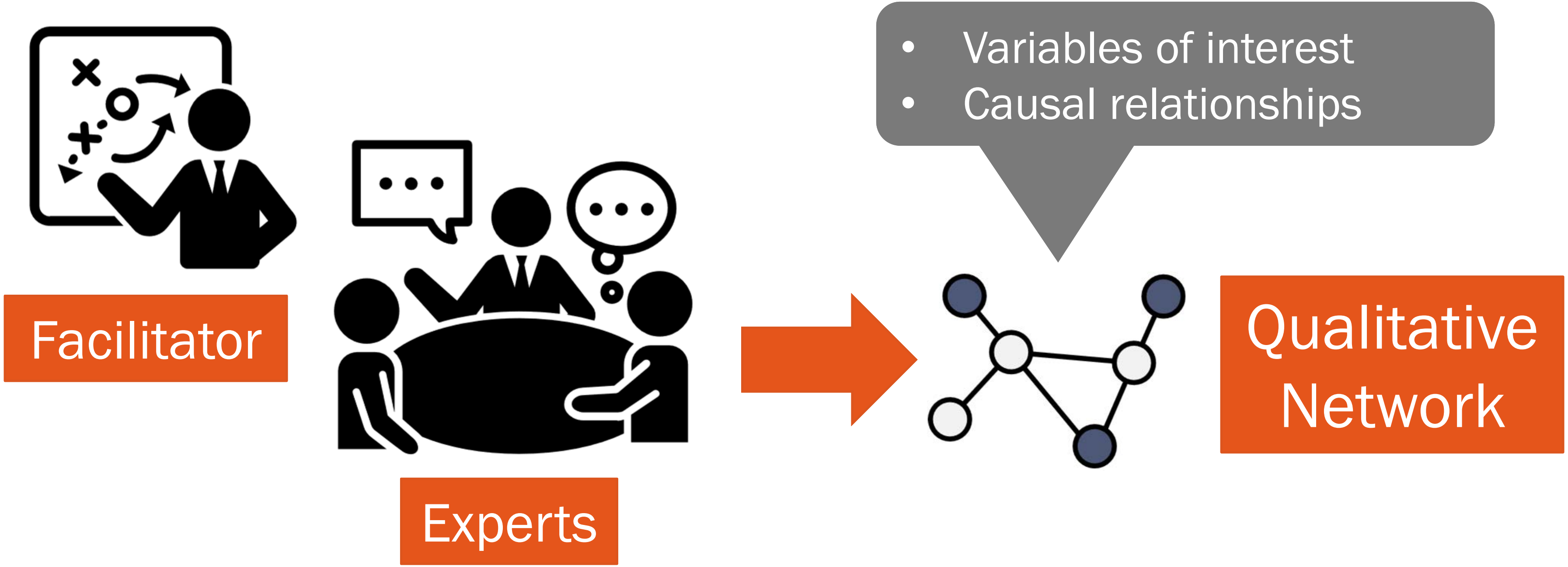
Constructing a Model for Decision Support

Source	Objective	Methodology	Technology
Data	Knowledge Discovery & Inference	Bayesian Networks	BAYESIALAB
Theory	Knowledge Elicitation	Delphi Method	BEKEE

Model Construction

Encoding what we know…

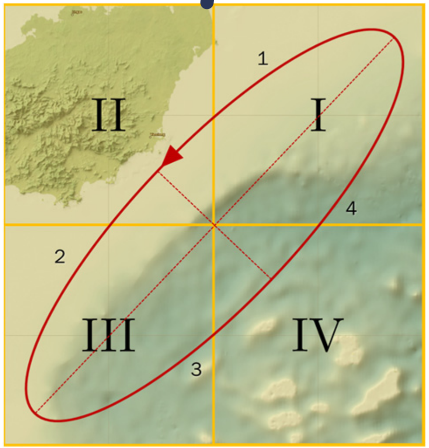
1. Brainstorming & Model Construction



Model Construction

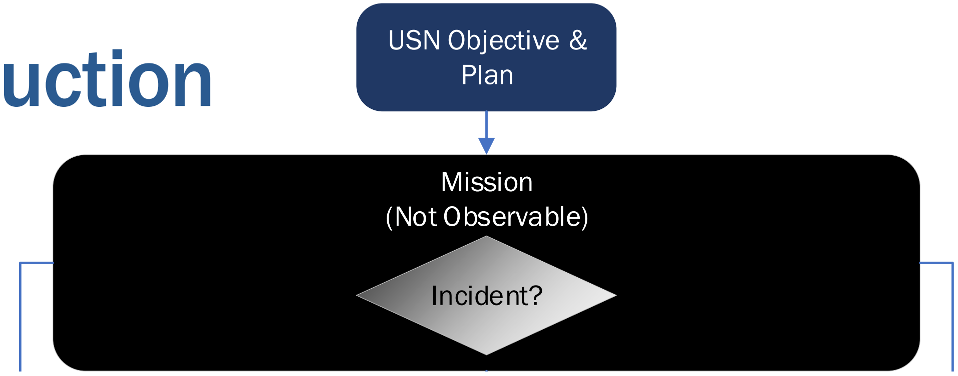
USN Objective & Plan

Reasoning Concept



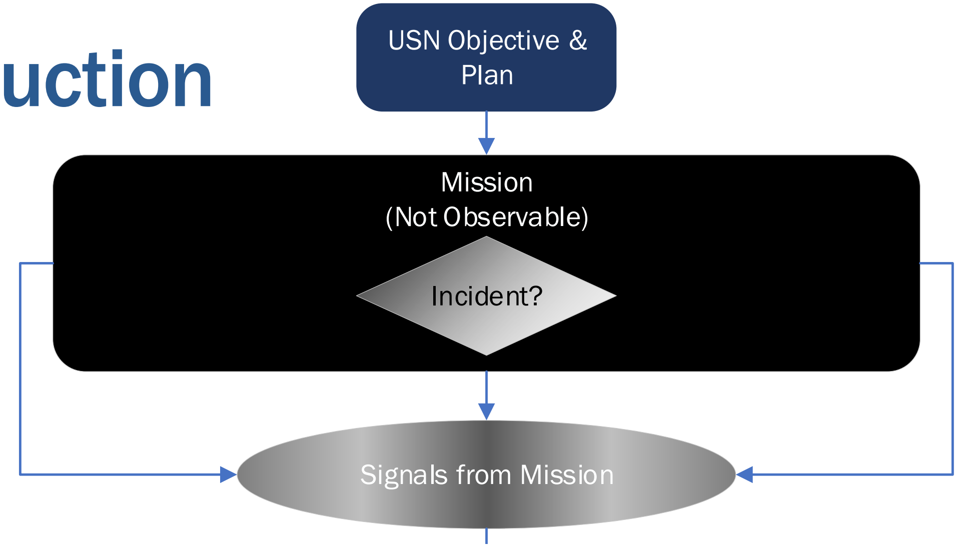
Model Construction

Reasoning Concept



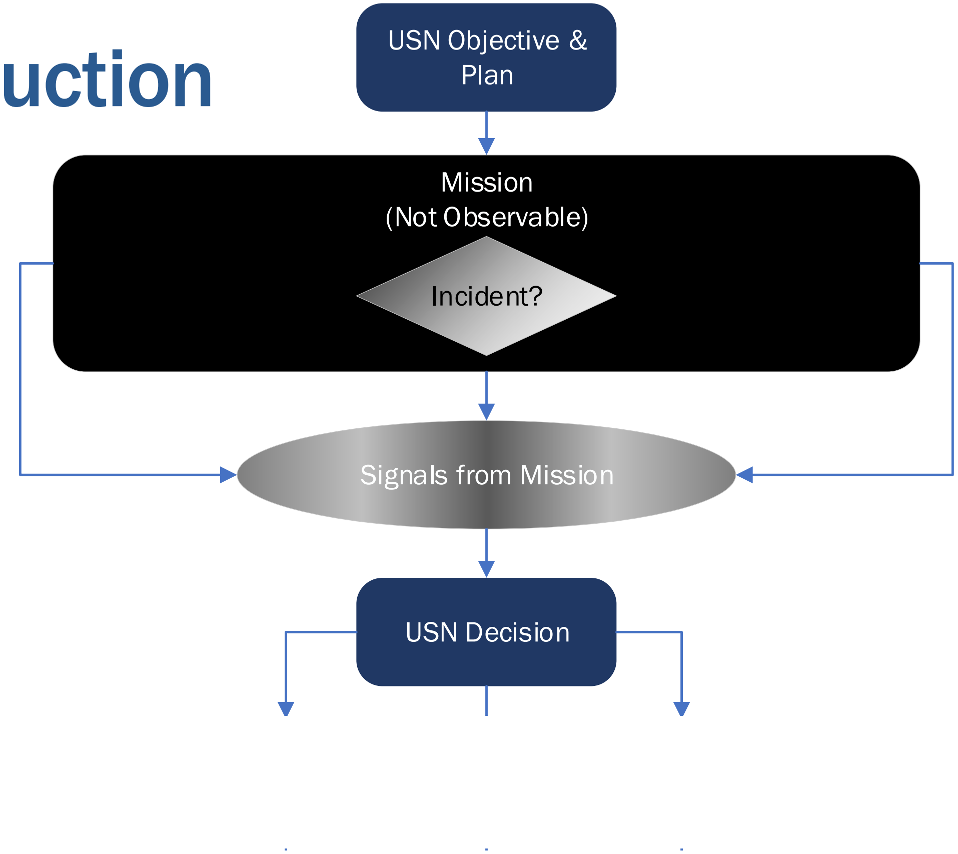
Model Construction

Reasoning Concept



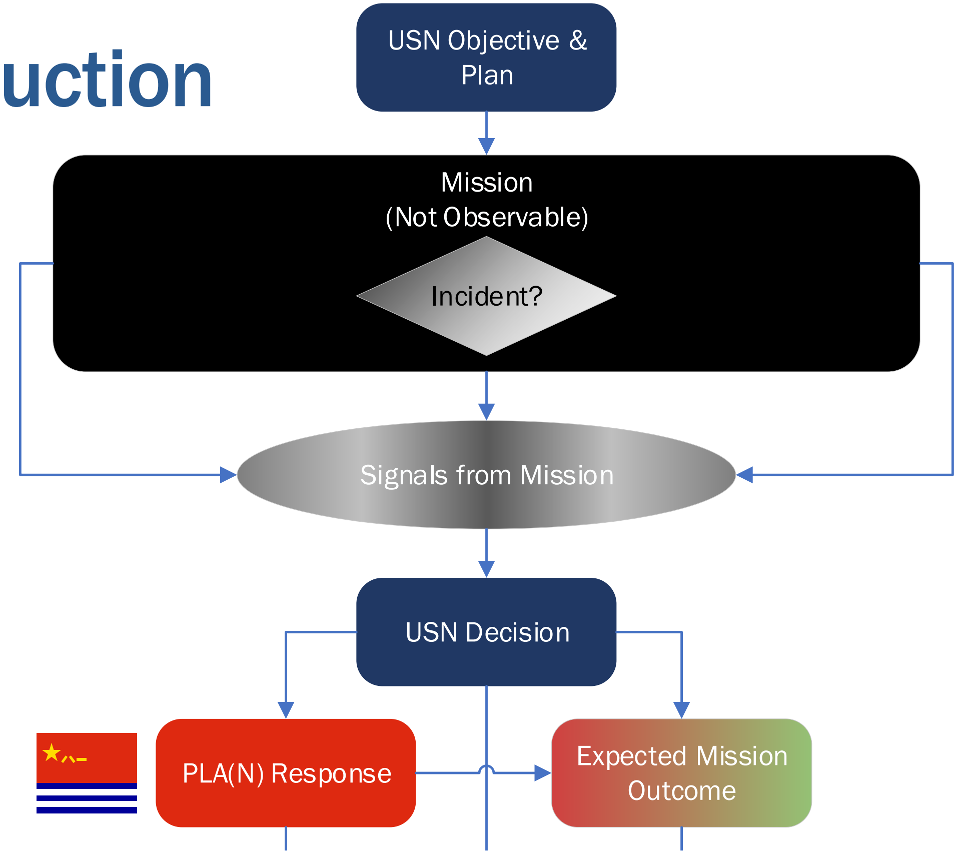
Model Construction

Reasoning Concept



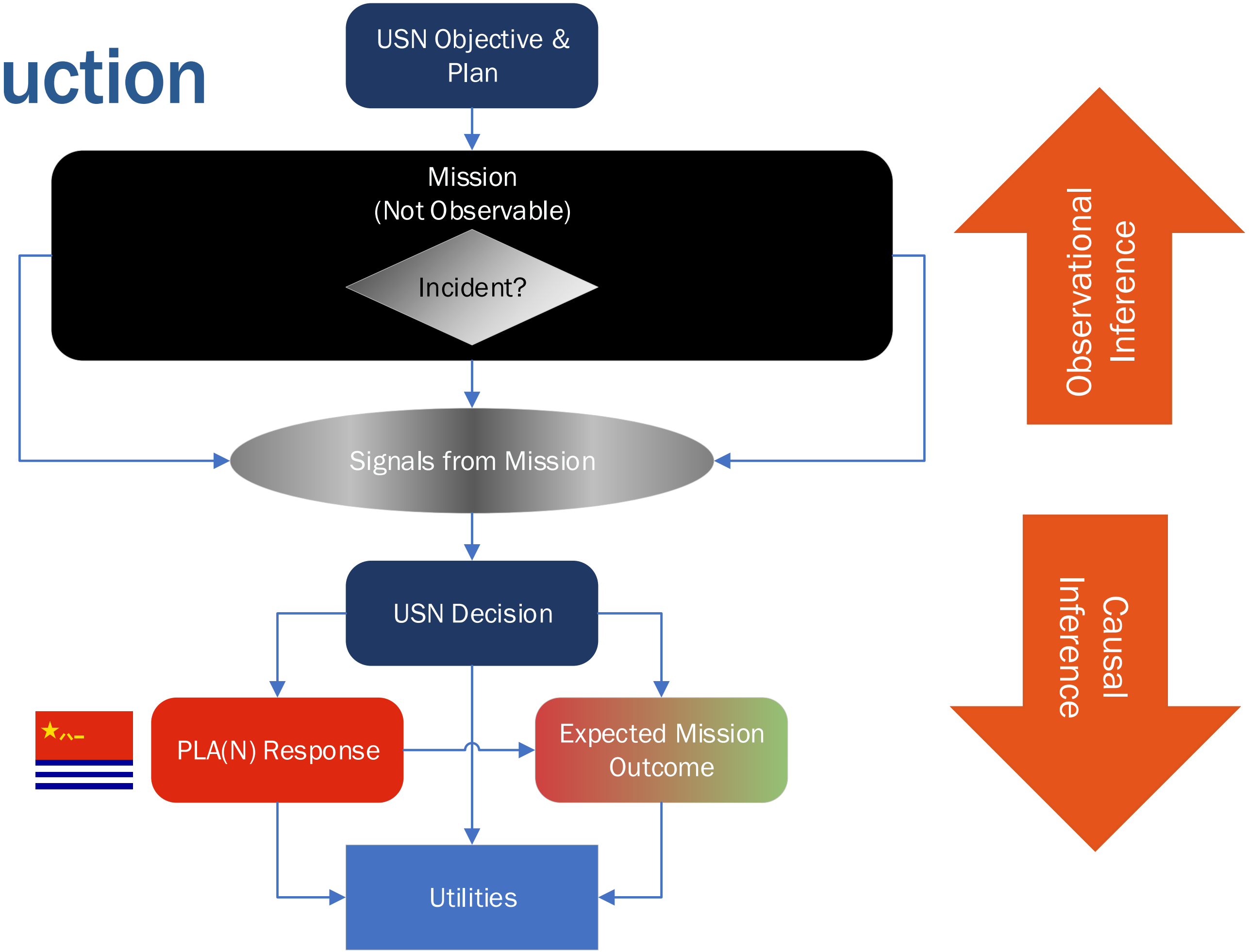
Model Construction

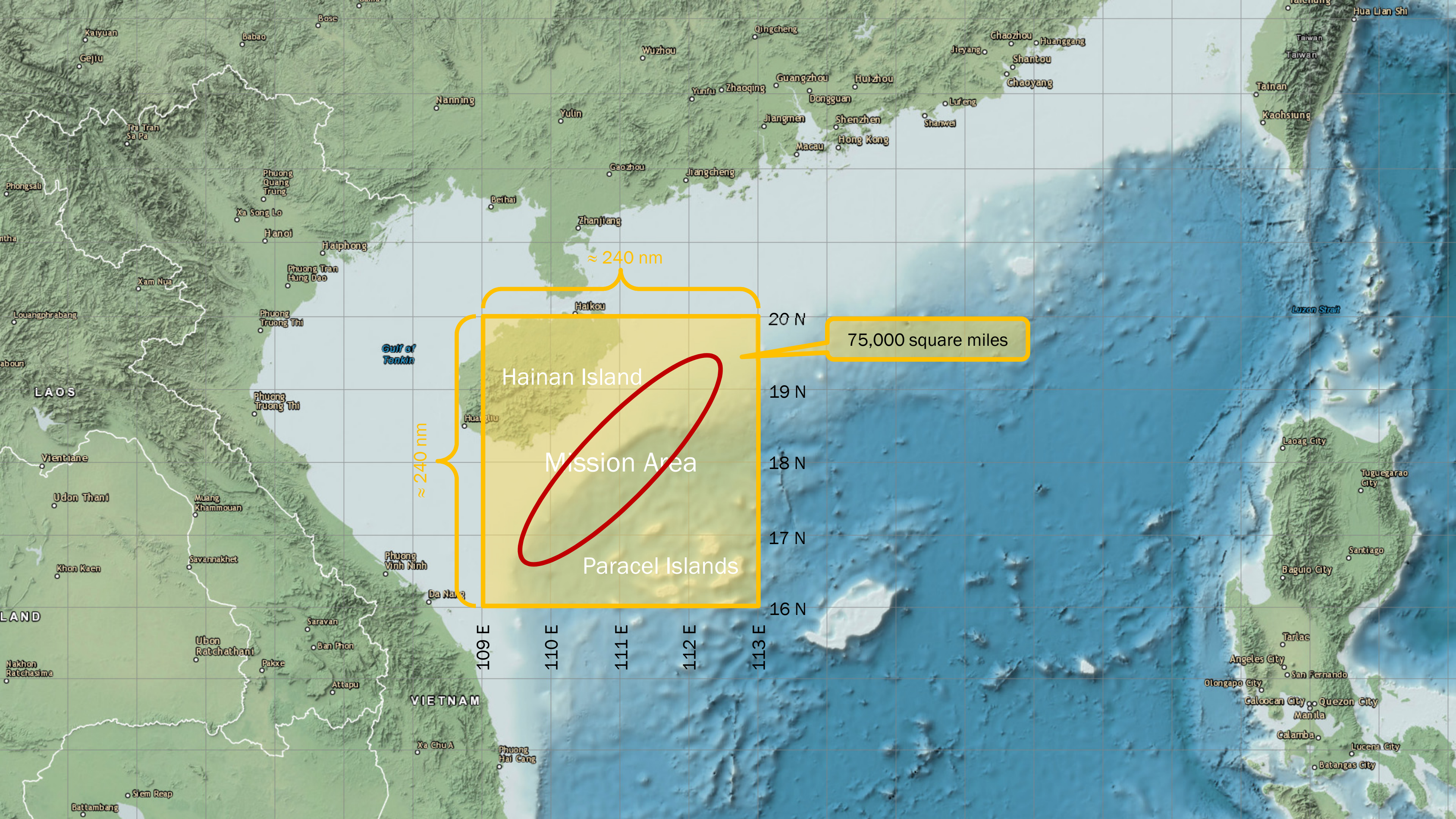
Reasoning Concept



Model Construction

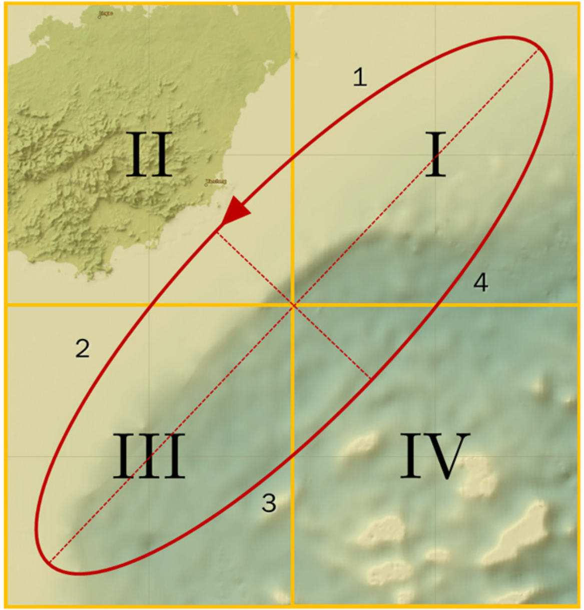
Reasoning Concept

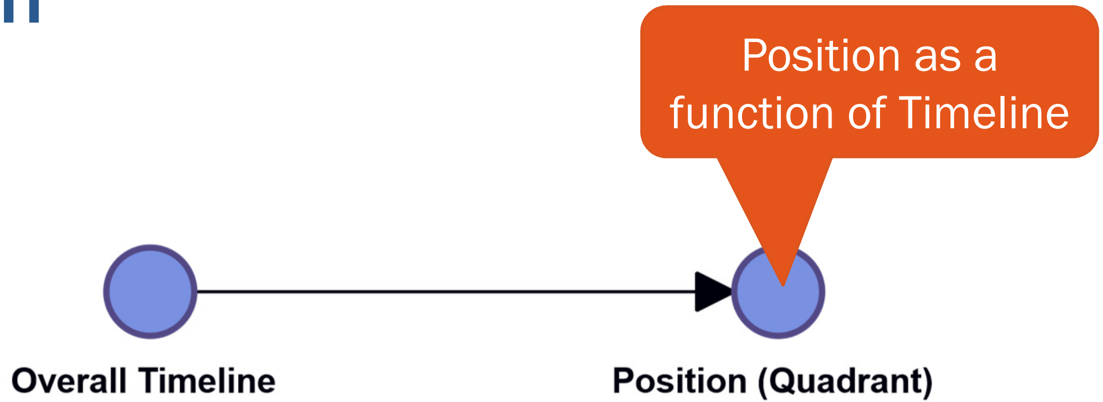



≈ 240 nm
≈ 240 nm
75,000 square miles
Hainan Island
Mission Area
Paracel Islands
20 N
19 N
18 N
17 N
16 N
109 E
110 E
111 E
112 E
113 E
Gulf of Tonkin
Luzon Strait
LAOS
VIETNAM
Hanoi
Haiphong
Nanning
Beihai
Zhanjiang
Haikou
Da Nang
Guangzhou
Hong Kong
Macau
Shenzhen
Kaohsiung
Tainan
Manila
Vientiane
Udon Thani

Model Construction

Encoding the Mission



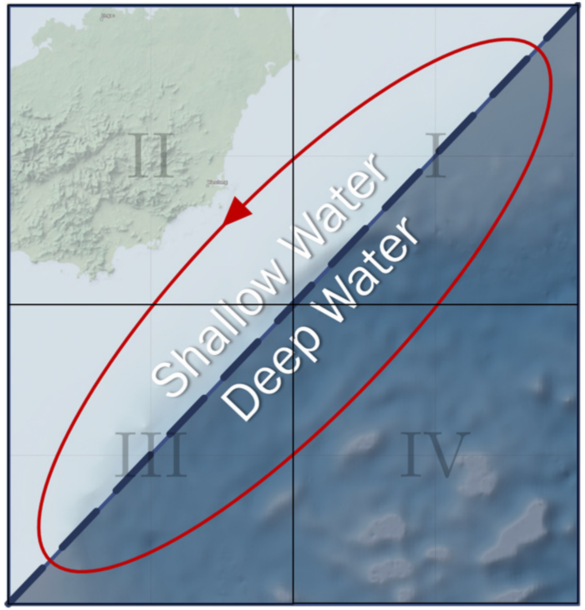


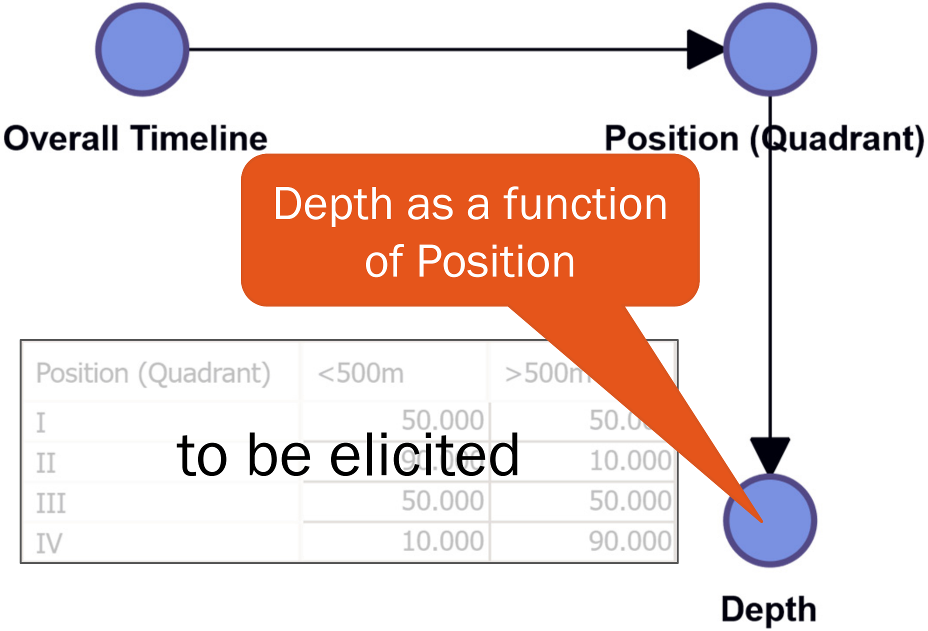
Overall Timeline	I	II	III	IV
1	40.000	40.000	10.000	10.000
2	10.000	40.000	40.000	10.000
3	10.000	10.000	40.000	40.000
4	40.000	10.000	10.000	40.000
5	50.000	16.667	16.667	16.667
6	60.000	13.333	13.333	13.333
7	70.000	10.000	10.000	10.000
8	80.000	6.667	6.667	6.667

to be elicited

Model Construction

Encoding the Mission

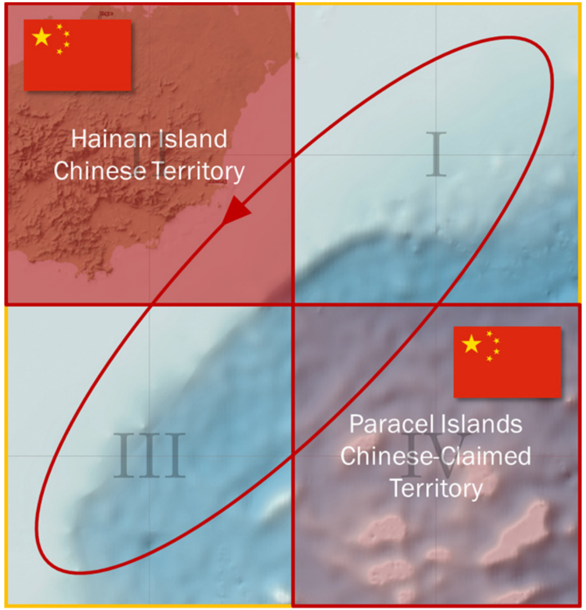




Position (Quadrant)	<500m	>500m
I	50.000	[illegible]
II	[illegible]	10.000
III	50.000	50.000
IV	10.000	90.000

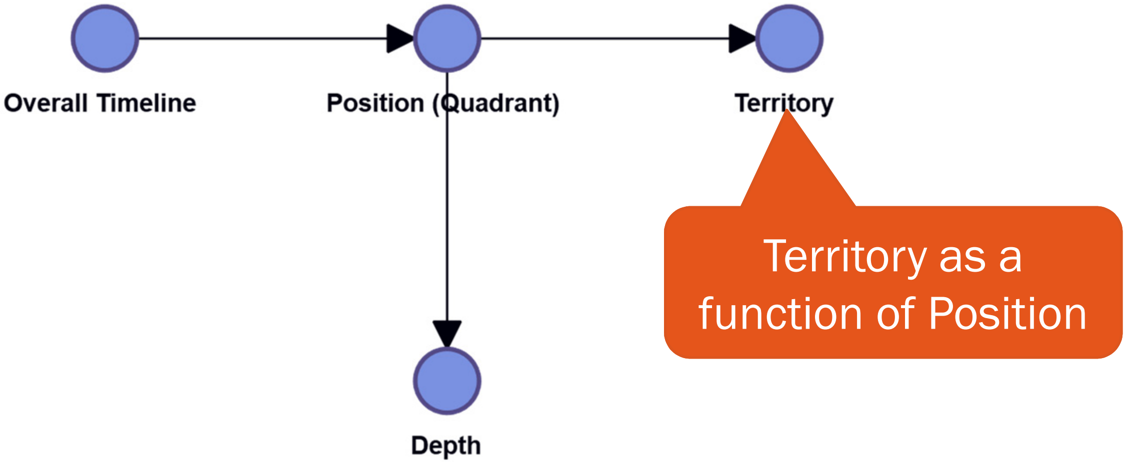
Model Construction

Encoding the Mission Dynamics



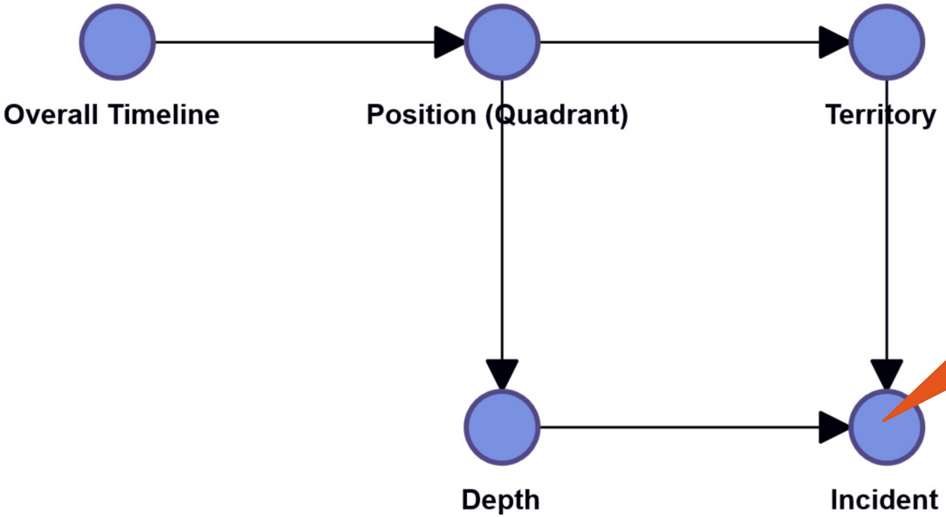
Position (Quadrant)	Chinese Territorial Waters	Chinese-Claimed Territorial Waters	International Waters
I	10.000	15.000	75.000
II	85.000	10.000	5.000
III	10.000	20.000	70.000
IV	10.000	80.000	10.000

to be elicited



Model Construction

Encoding the Mission



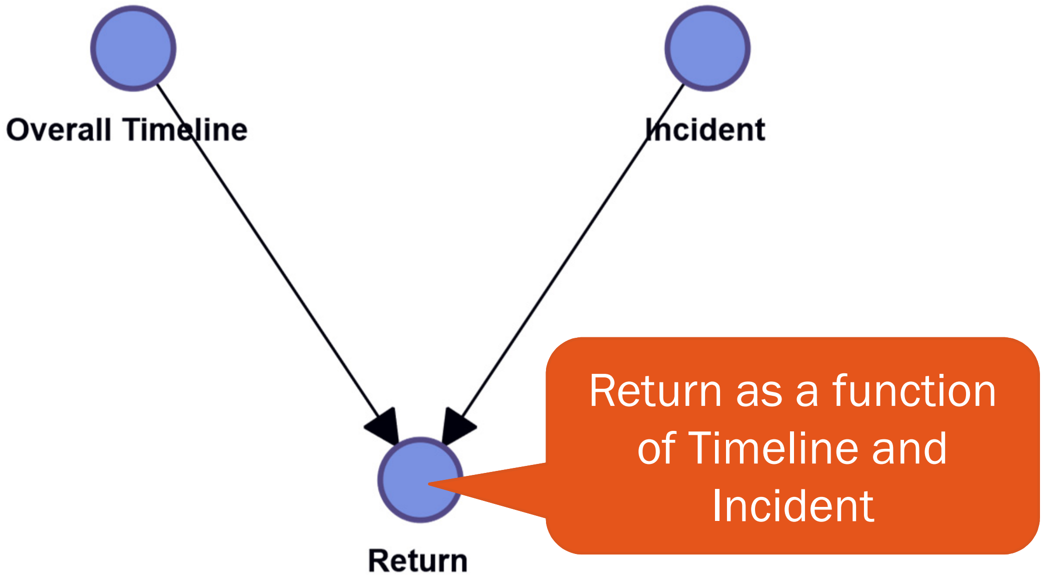
Incident as a function of Territory and Depth

Territory	Depth	False	True
Chinese Territorial Waters	<500m	95.000	5.000
	>500m	99.000	1.000
Chinese-Claimed Territorial Waters	<500m	97.000	3.000
	>500m	99.000	1.000
International Waters	<500m	99.000	1.000
	>500m	99.500	0.500

to be elicited

Model Construction

Encoding the Mission

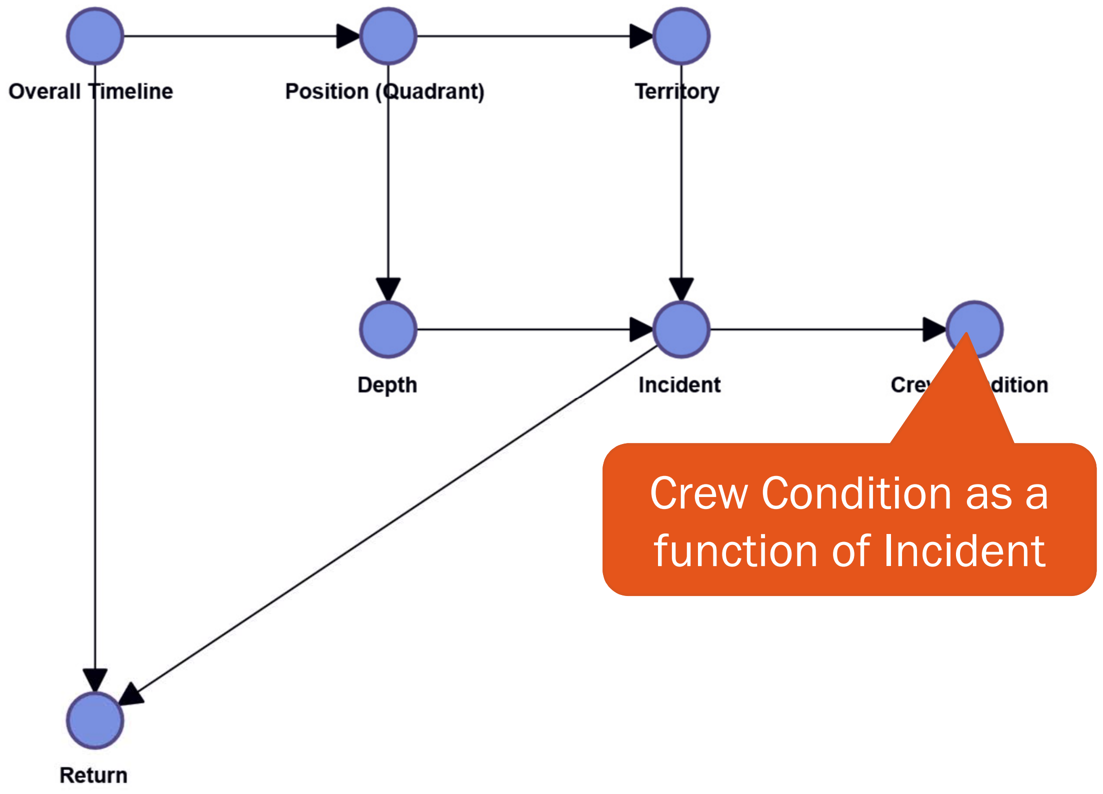


Incident	Overall Timeline	False	True
False	1	75.000	25.000
	2	50.000	50.000
	3	25.000	75.000
	4	10.000	90.000
	5	5.000	95.000
	6	4.000	96.000
	7	3.000	97.000
	8	1.000	99.000
True	1	90.000	10.000
	2	91.000	9.000
	3	92.000	8.000
	4	93.000	7.000
	5	94.000	6.000
	6	95.000	5.000
	7	96.000	4.000
	8	97.000	3.000

to be elicited

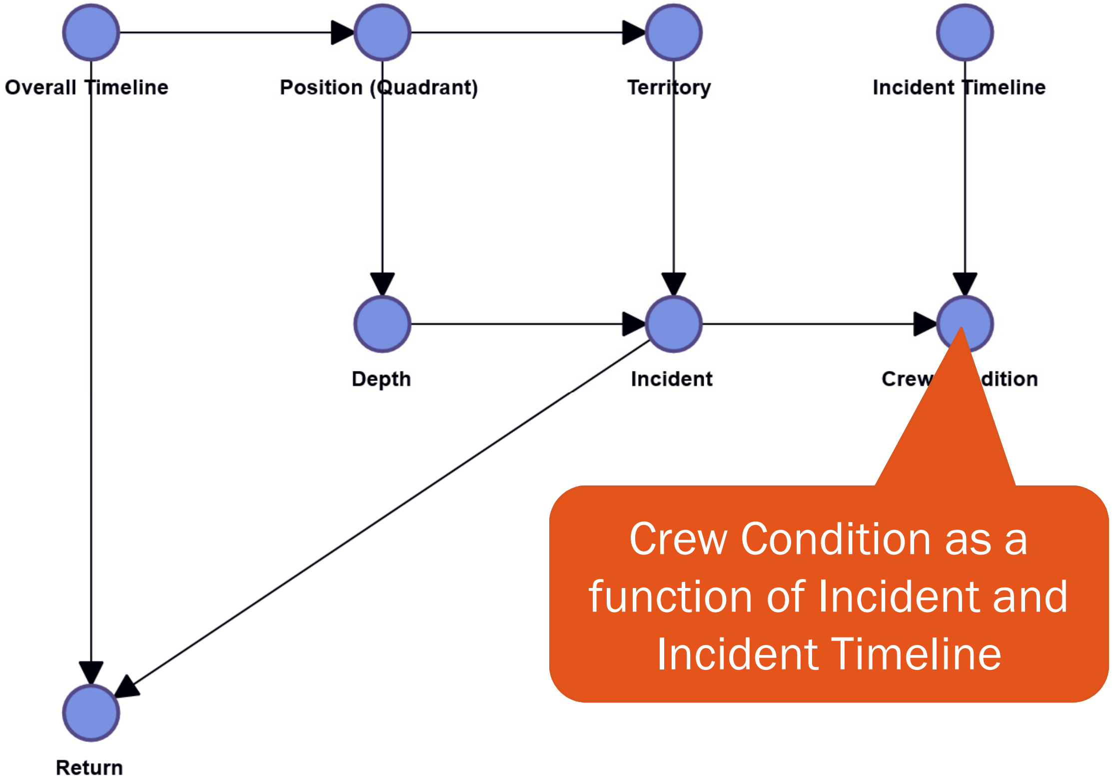
Model Construction

Encoding the Mission



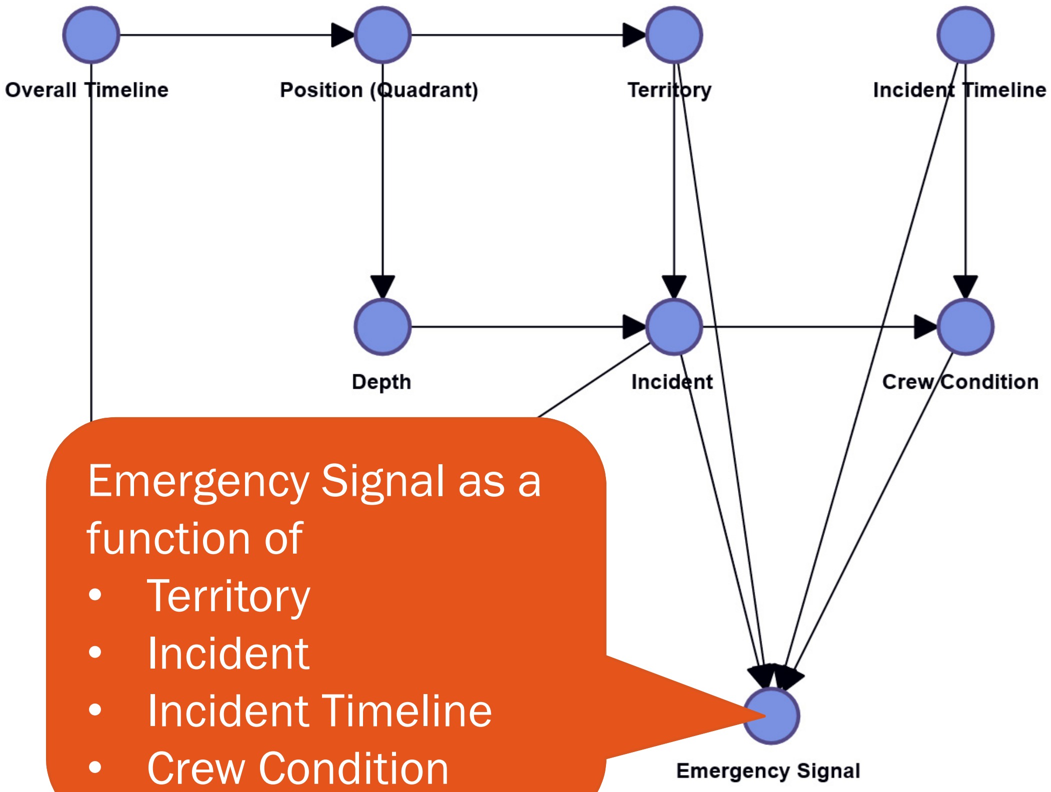
Model Construction

Encoding the Mission



Model Construction

Encoding the Mission

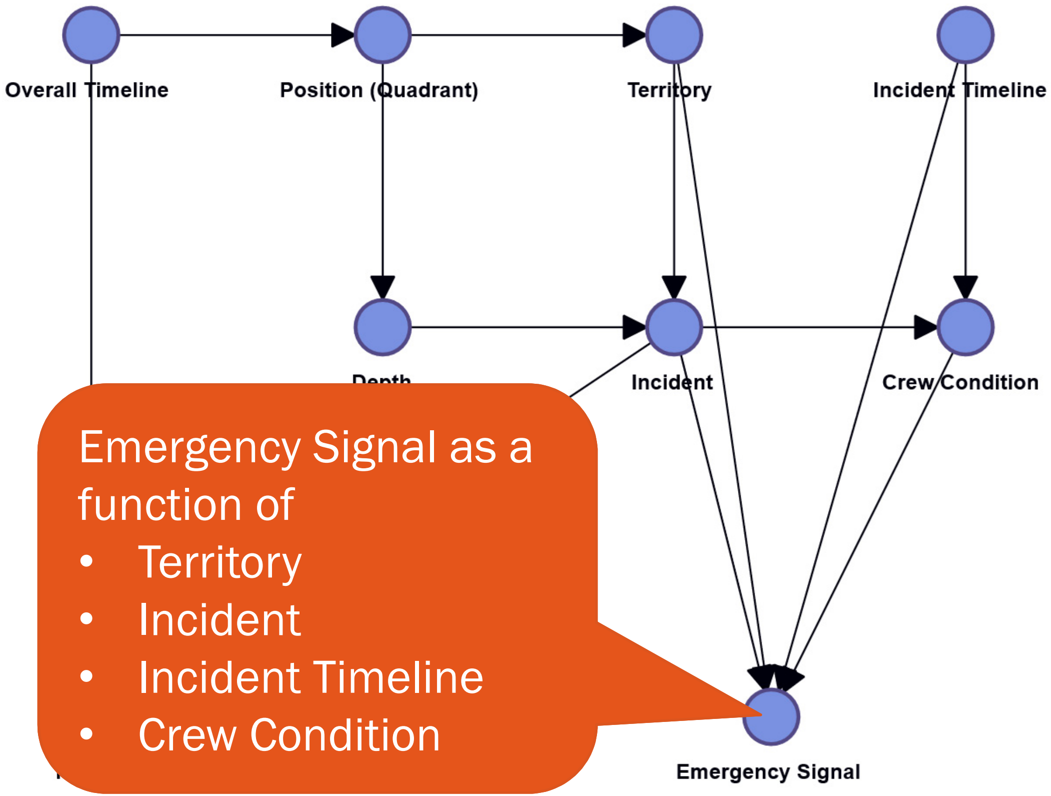


Emergency Signal as a function of

- Territory
- Incident
- Incident Timeline
- Crew Condition

Model Construction

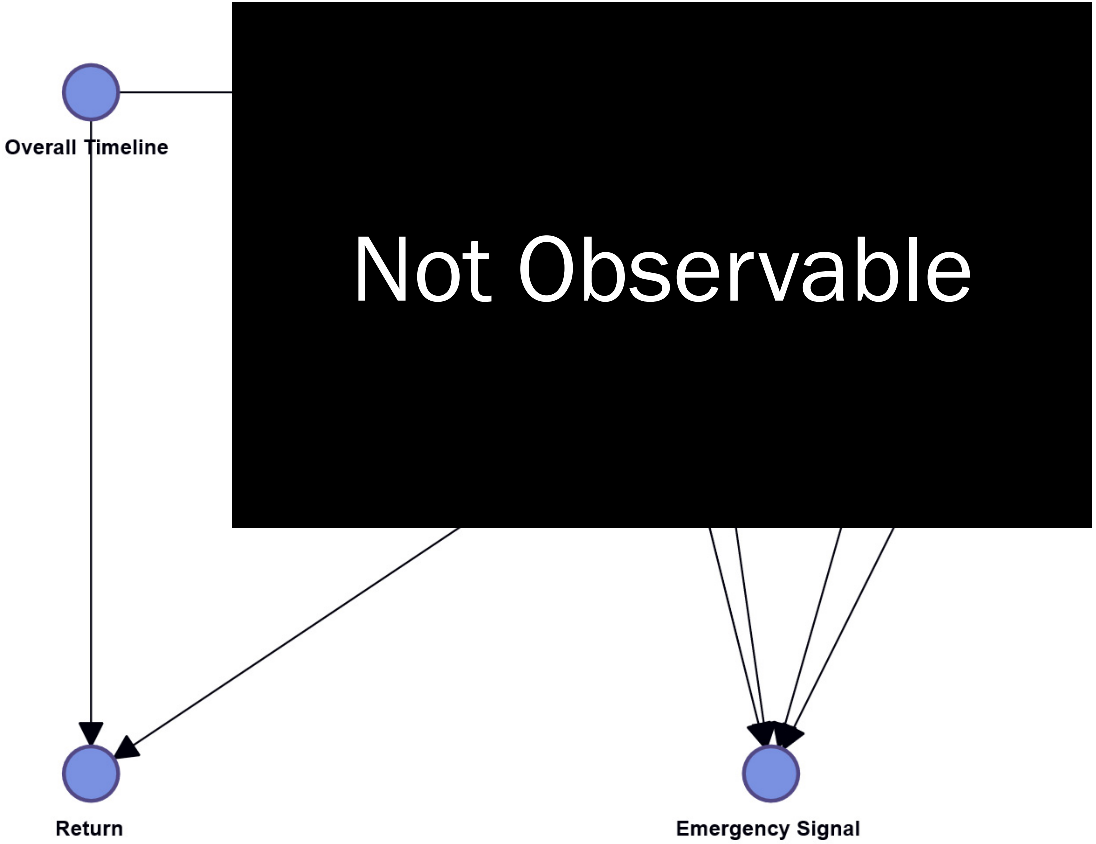
Encoding the Mission



Model Construction

Encoding the Mission

- We need to infer the unobservable variables from the observable ones:
    - Time
    - Return
    - Emergency Signal

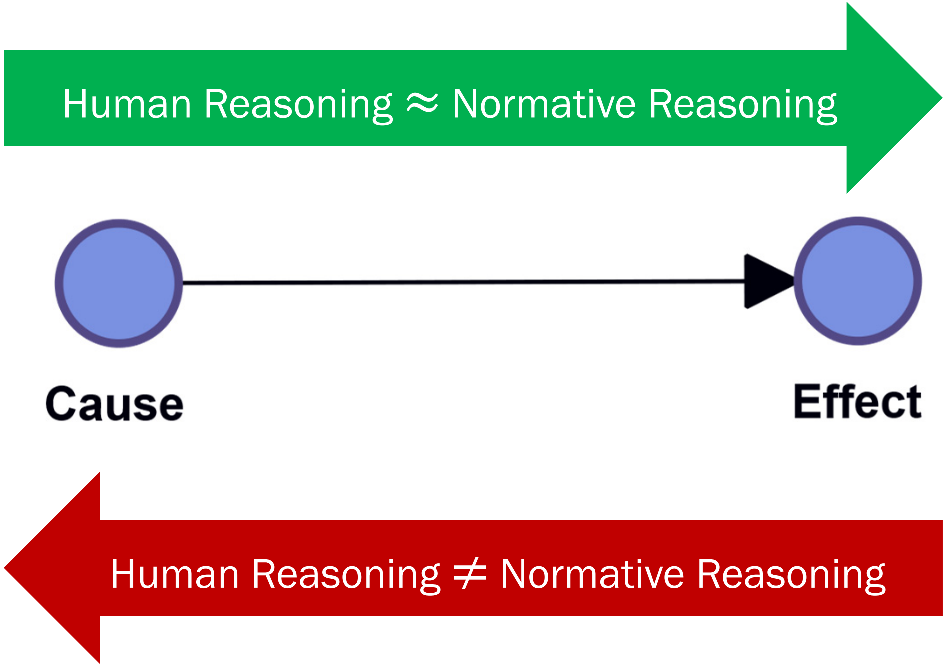


Model Construction

Can't we intuitively reason just the same way?

Why is this so important?

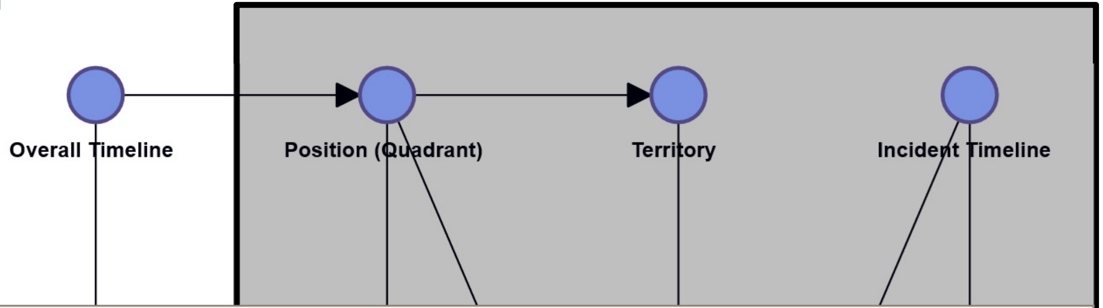
Human Cognitive Limitations and Biases Under Uncertainty



FALLACIES

Model Construction

- 16 Influence Paths to Crew Condition:

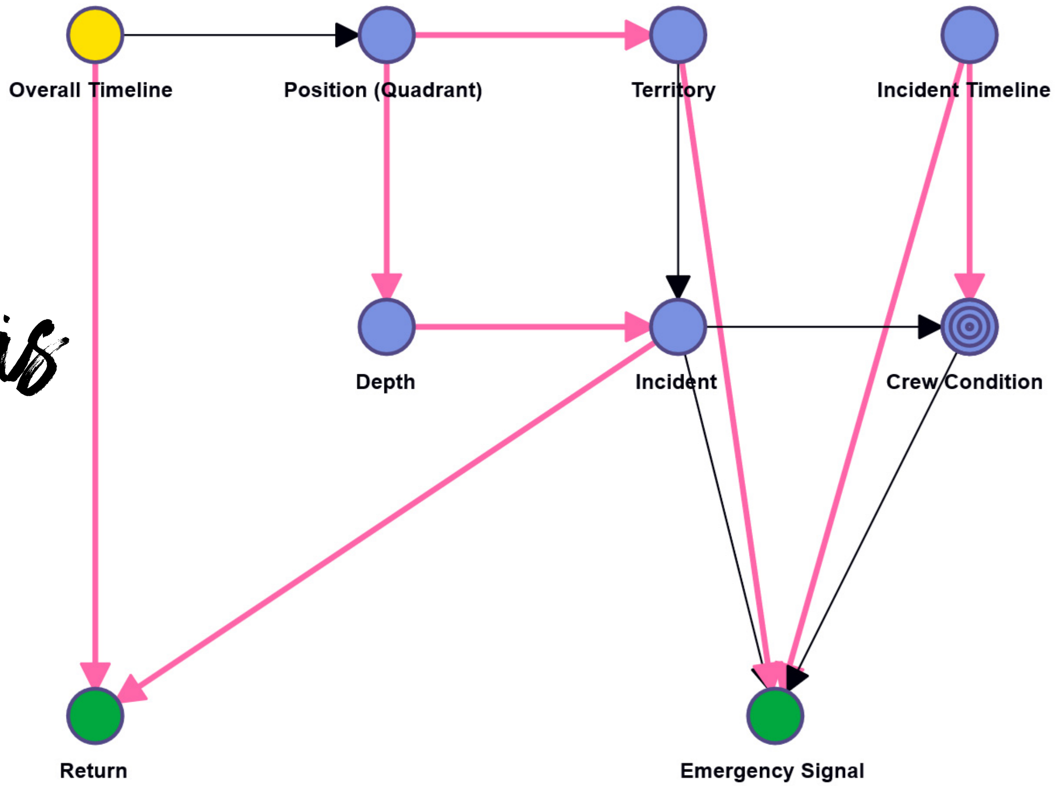


Path	Causal	Length	Score	Description
Path 0	☐	6	27.6703132	Overall Timeline -> Return <- Incident <- Territory <- Position (Quadrant) -> Emergency Signal <- Crew Condition
Path 1	☐	7	40.3283899	Overall Timeline -> Return <- Incident <- Territory <- Position (Quadrant) -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 2	☐	6	28.9755482	Overall Timeline -> Return <- Incident <- Depth <- Position (Quadrant) -> Emergency Signal <- Crew Condition
Path 3	☐	7	41.6336248	Overall Timeline -> Return <- Incident <- Depth <- Position (Quadrant) -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 4	☐	4	21.5221298	Overall Timeline -> Return <- Incident -> Emergency Signal <- Crew Condition
Path 5	☐	5	34.1802064	Overall Timeline -> Return <- Incident -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 6	☐	3	6.5862831	Overall Timeline -> Return <- Incident -> Crew Condition
Path 7	☐	3	17.1274977	Overall Timeline -> Position (Quadrant) -> Emergency Signal <- Crew Condition
Path 8	☐	4	15.6225698	Overall Timeline -> Position (Quadrant) -> Emergency Signal <- Incident -> Crew Condition
Path 9	☐	4	29.7855744	Overall Timeline -> Position (Quadrant) -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 10	☐	5	27.9877014	Overall Timeline -> Position (Quadrant) -> Depth -> Incident -> Emergency Signal <- Crew Condition
Path 11	☐	6	40.6457781	Overall Timeline -> Position (Quadrant) -> Depth -> Incident -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 12	☑	4	13.0518547	Overall Timeline -> Position (Quadrant) -> Depth -> Incident -> Crew Condition
Path 13	☐	5	26.6824665	Overall Timeline -> Position (Quadrant) -> Territory -> Incident -> Emergency Signal <- Crew Condition
Path 14	☐	6	39.3405431	Overall Timeline -> Position (Quadrant) -> Territory -> Incident -> Emergency Signal <- Incident Timeline -> Crew Condition
Path 15	☑	4	11.7466197	Overall Timeline -> Position (Quadrant) -> Territory -> Incident -> Crew Condition

Model Construction

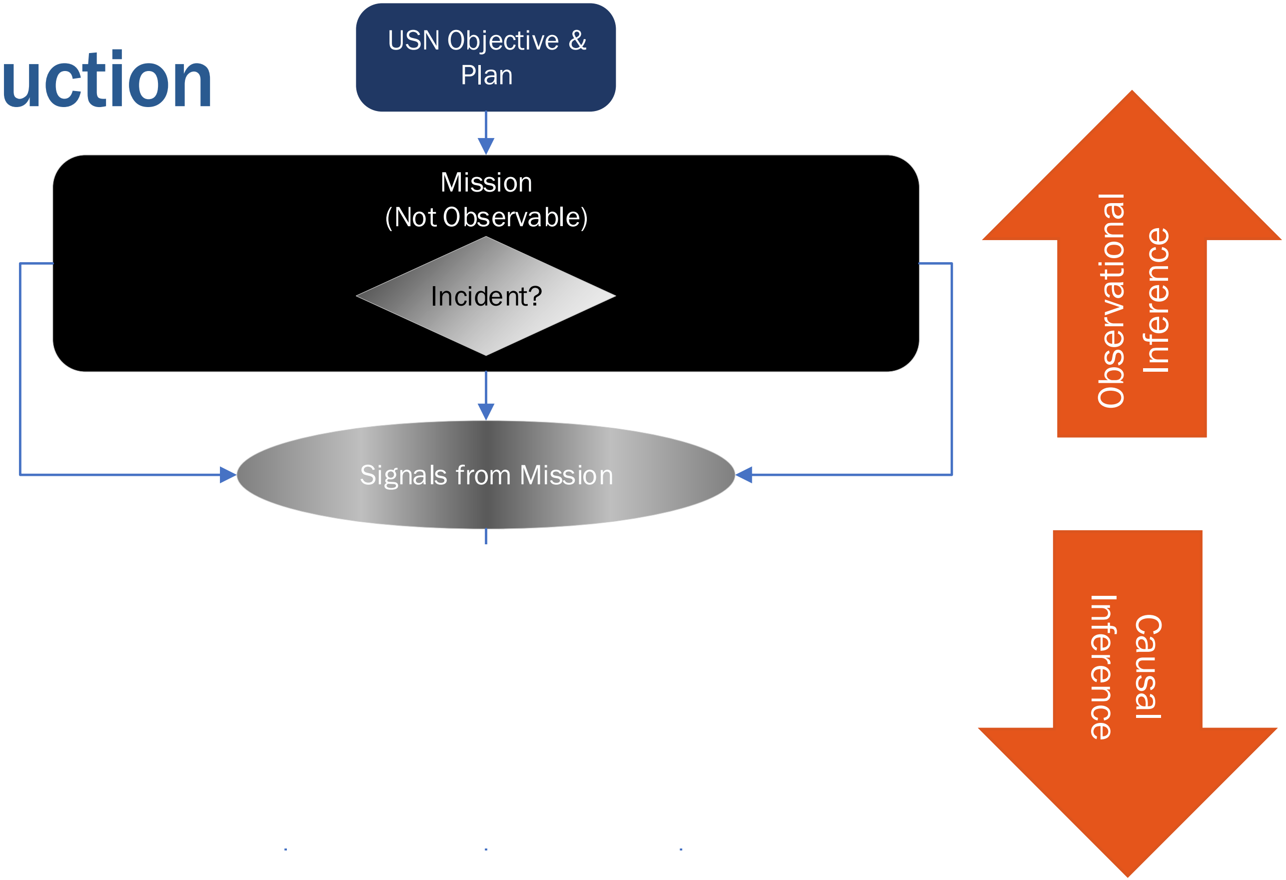
- One of the 16 influence paths:

So, can you do this is your head?



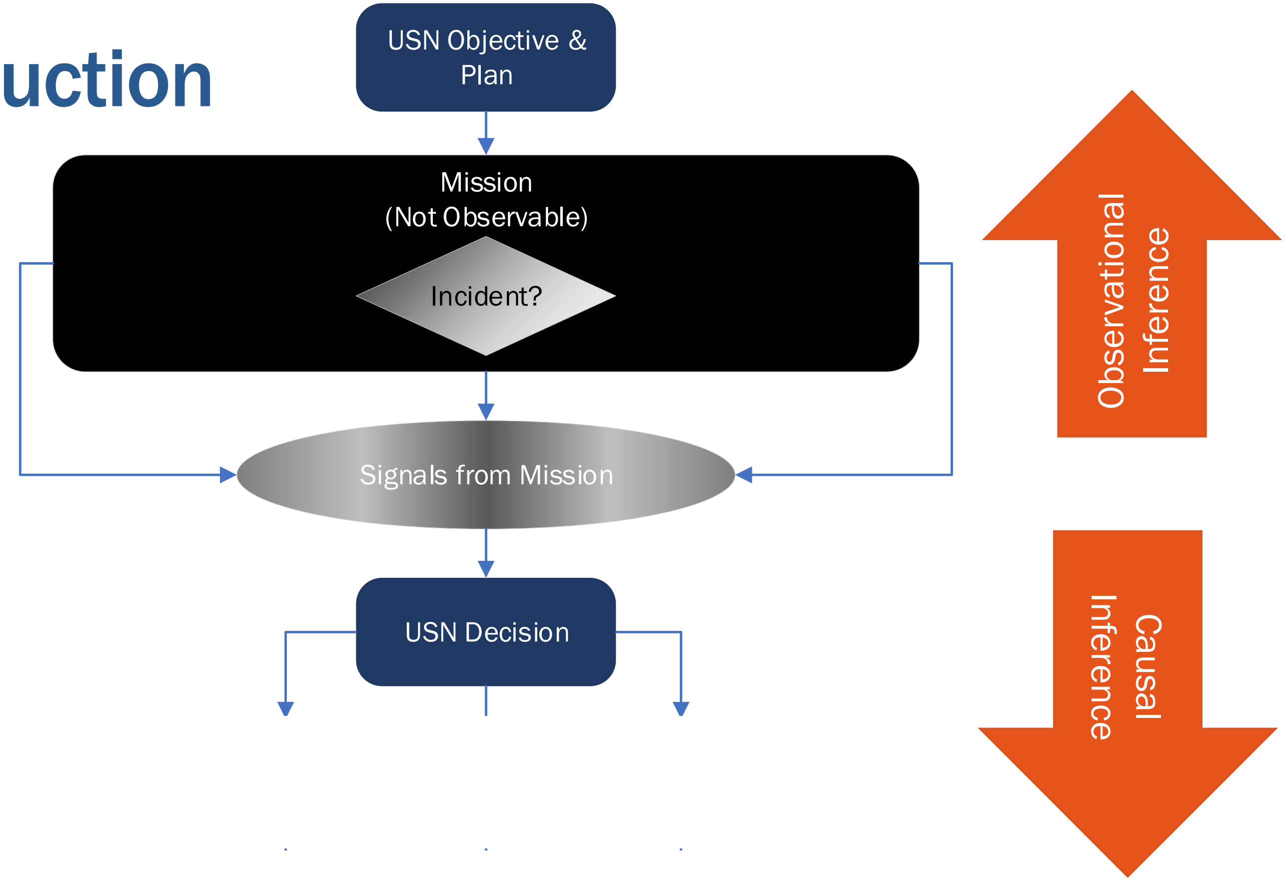
Model Construction

Reasoning Concept



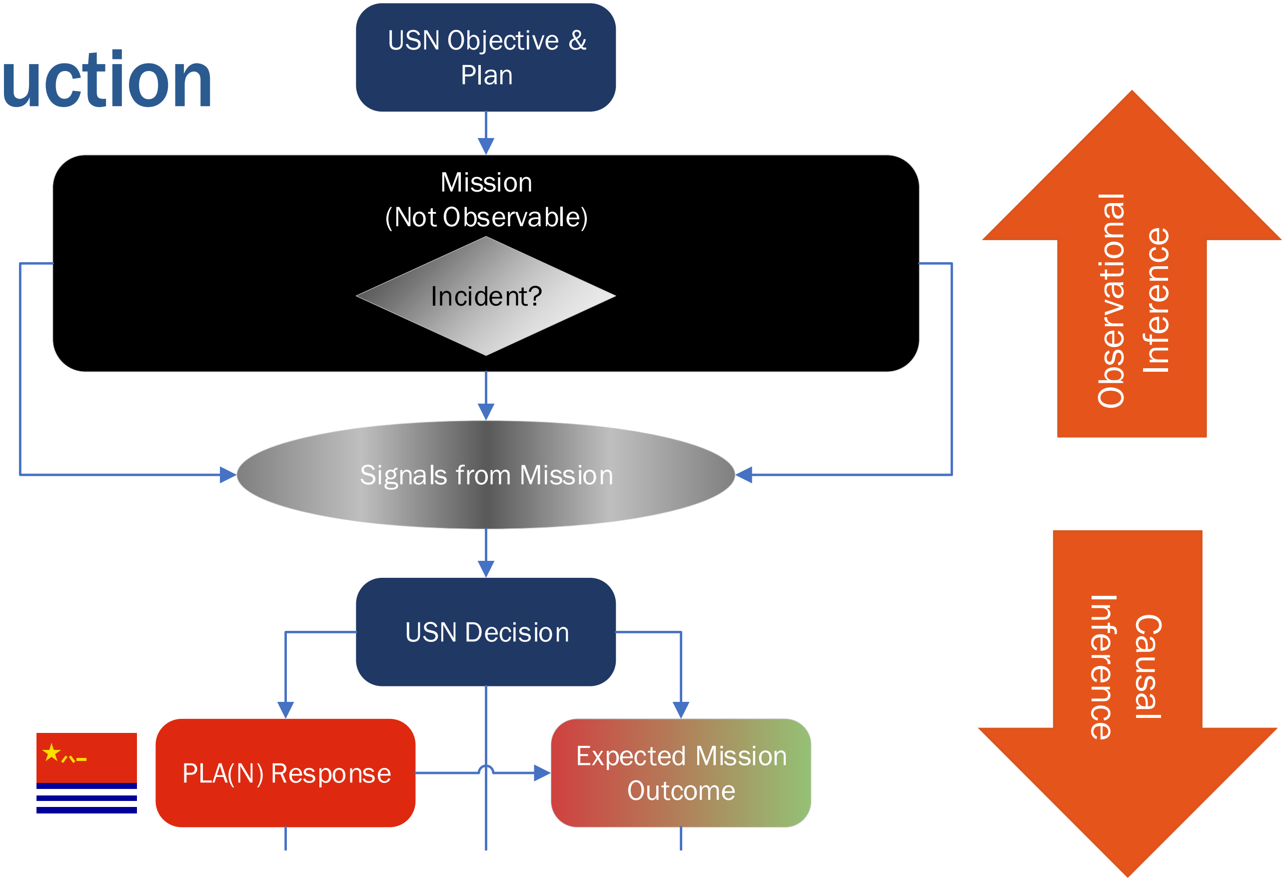
Model Construction

Reasoning Concept



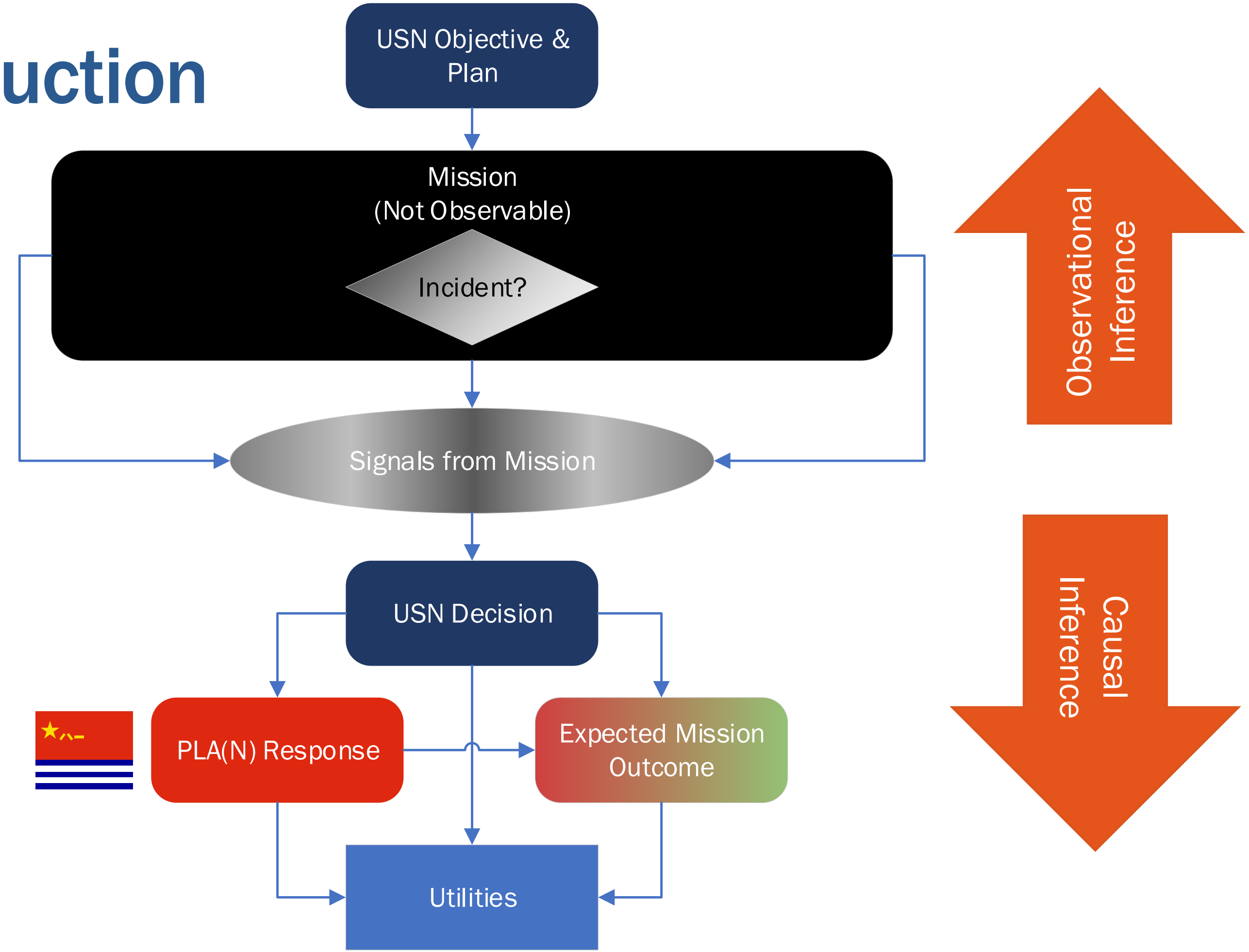
Model Construction

Reasoning Concept



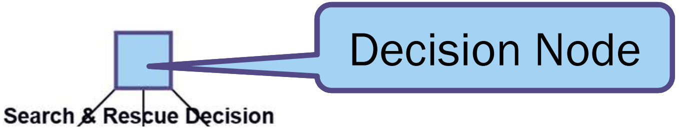
Model Construction

Reasoning Concept




UNDERSEA
RESCUE
COMMAND

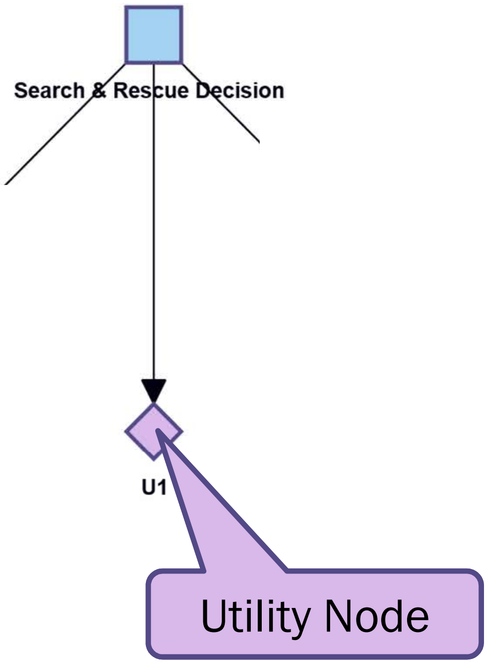
Model Construction



Modeling the Decision

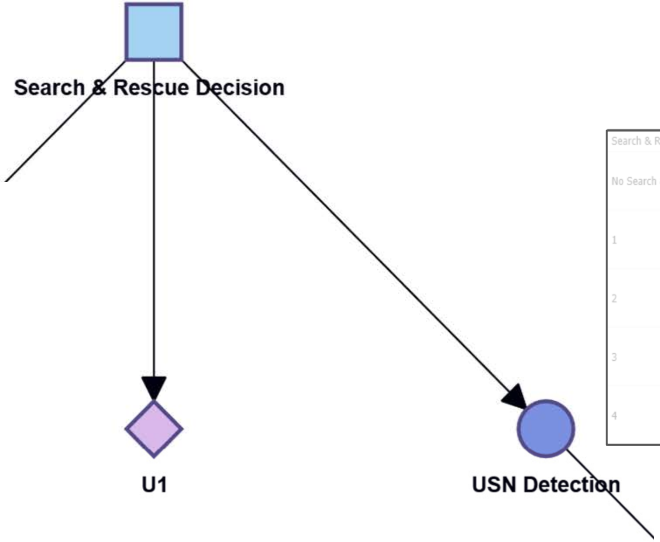
Model Construction

Modeling the Decision



Model Construction

Modeling the Decision

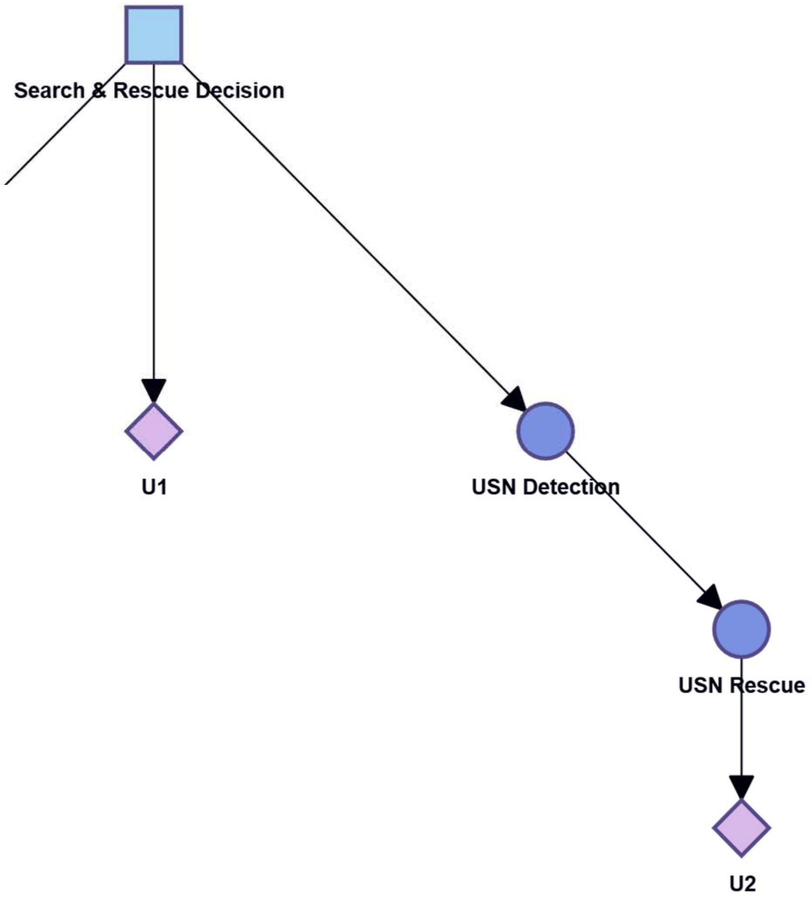


Search & Rescue Decision	Position (Quadrant)	False	True
No Search & Rescue Effort	I	95.000	5.000
	II	95.000	5.000
	III	95.000	5.000
	IV	95.000	5.000
1	I	20.000	80.000
	II	95.000	5.000
	III	95.000	5.000
	IV	95.000	5.000
2	[illegible]	95.000	5.000
	II	30.000	70.000
	III	[illegible]	5.000
	[illegible]	[illegible]	5.000
3	[illegible]	[illegible]	5.000
	[illegible]	[illegible]	5.000
	III	20.000	80.000
	IV	95.000	5.000
4	I	95.000	5.000
	II	95.000	5.000
	III	95.000	5.000
	IV	25.000	75.000

to be elicited

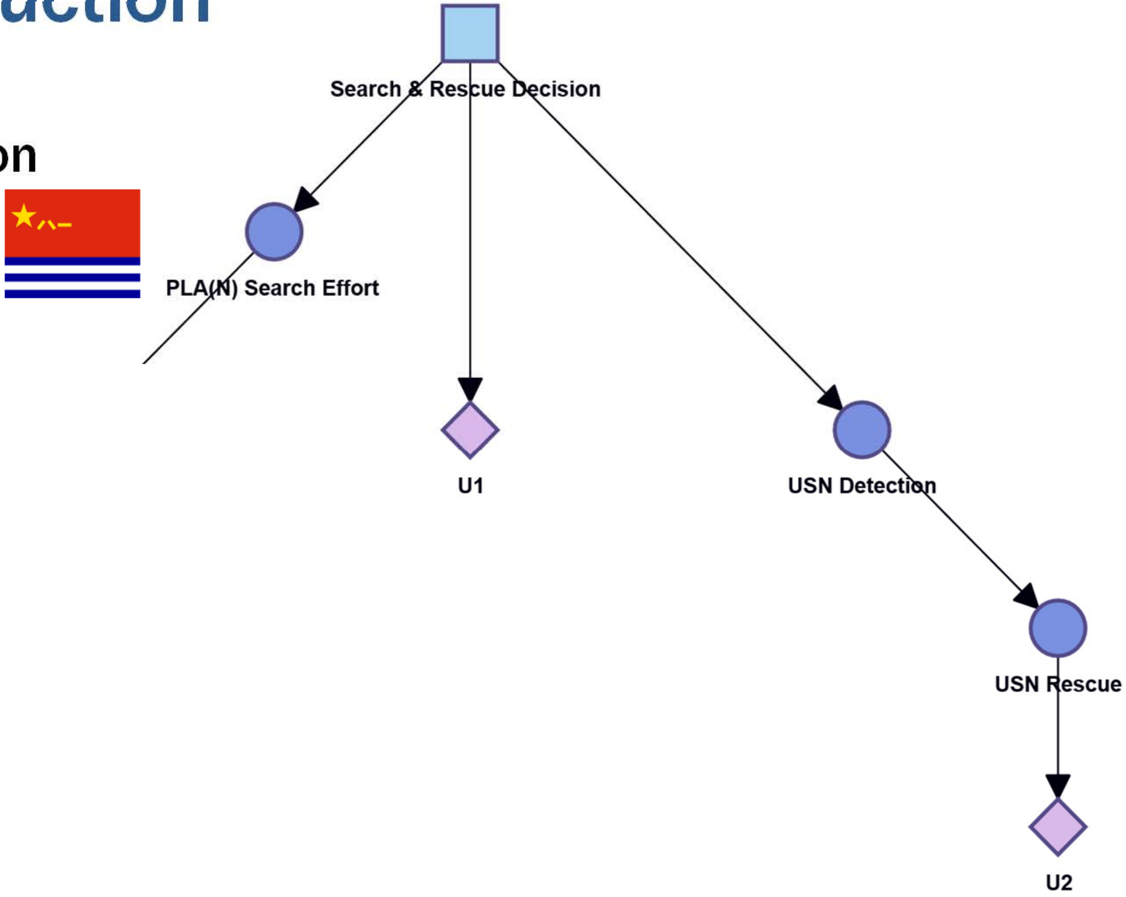
Model Construction

Modeling the Decision



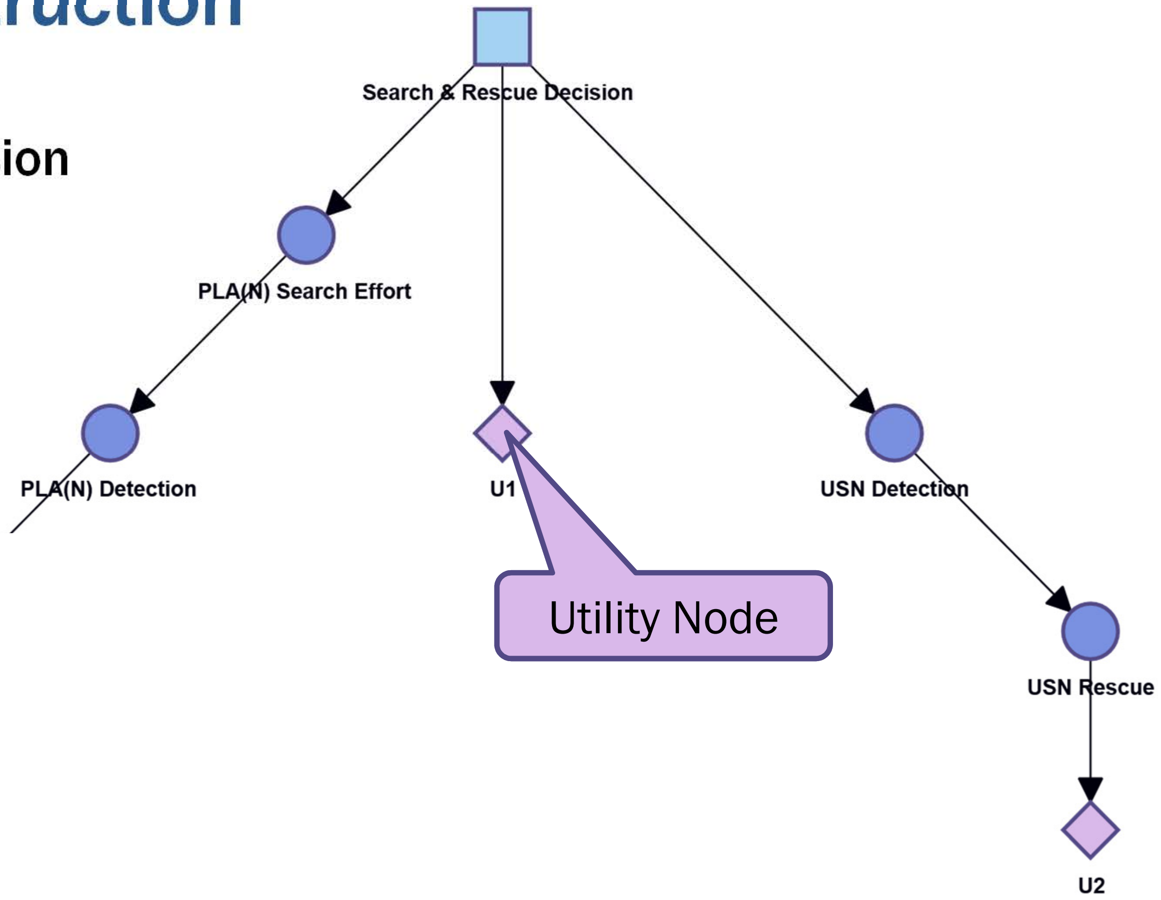
Model Construction

Modeling the Decision



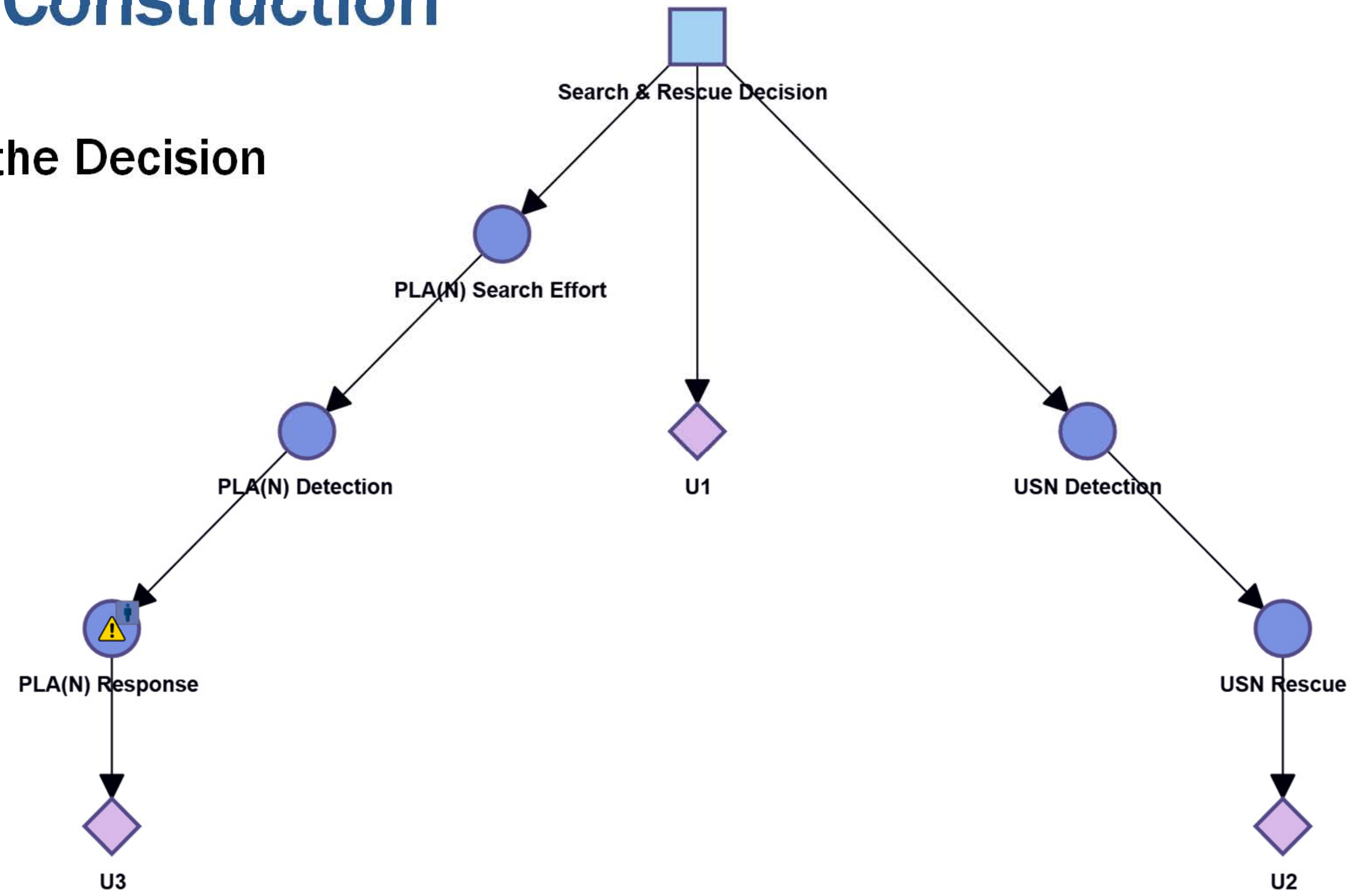
Model Construction

Modeling the Decision



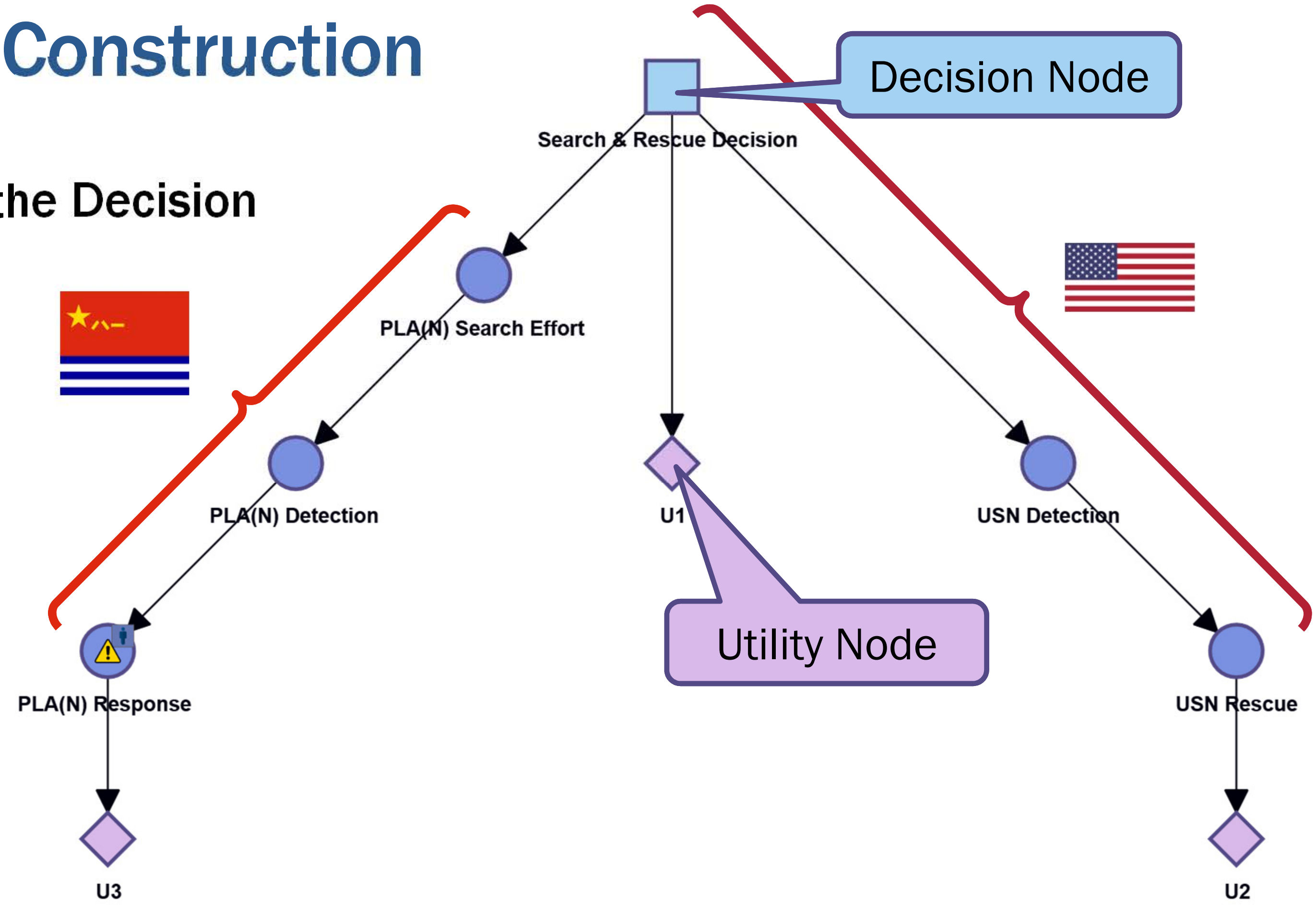
Model Construction

Modeling the Decision



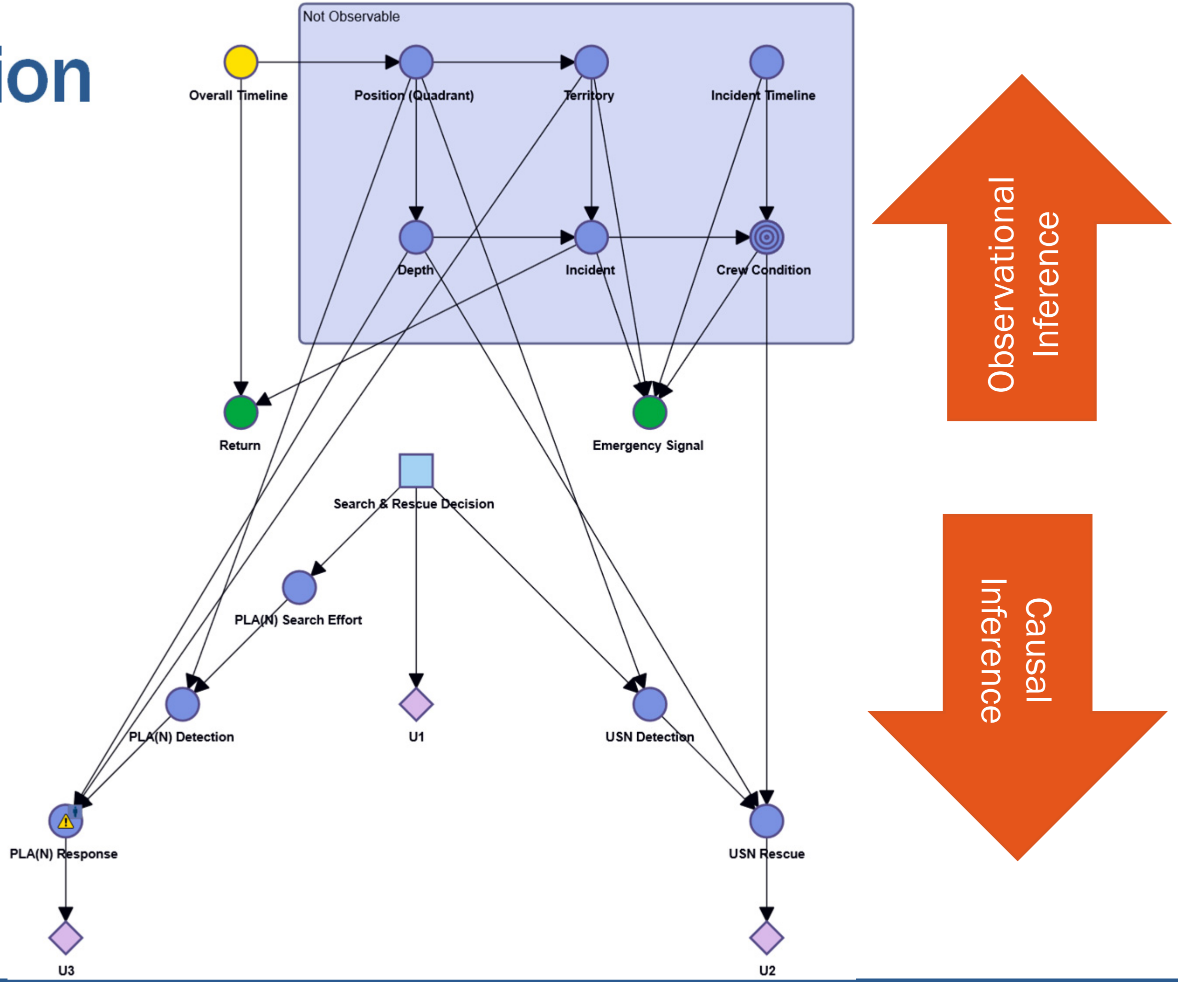
Model Construction

Modeling the Decision



Model Construction

Combining the Models



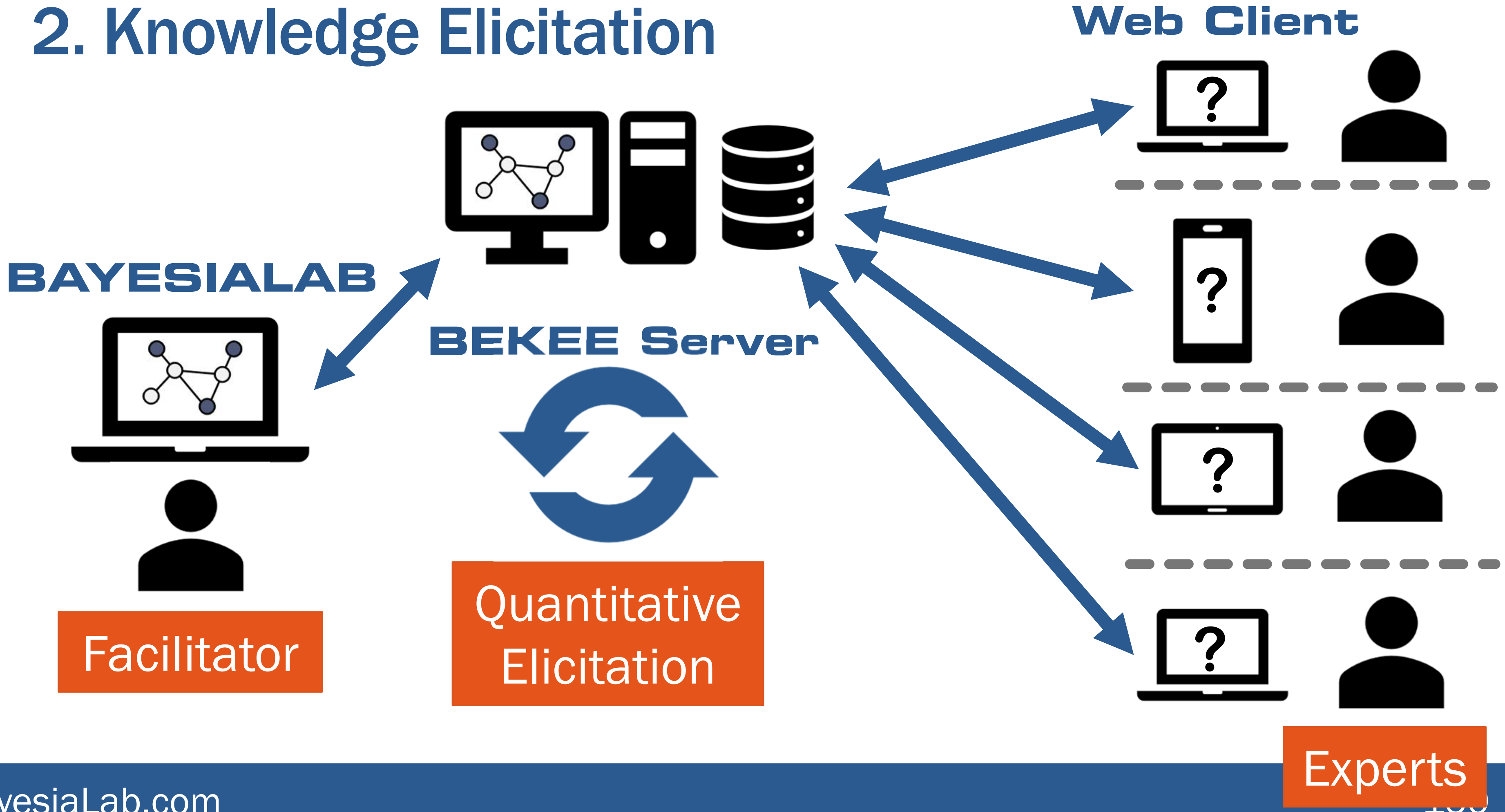
Model Construction

Finding the Optimal Decision

- Scenarios based on dummy data:

Day	Emergency Signal	Optimal Decision
5	TRUE	1
5	FALSE	1
6	TRUE	3
6	FALSE	No Search
7	TRUE	2
7	FALSE	No Search
8	TRUE	2
8	FALSE	No Search

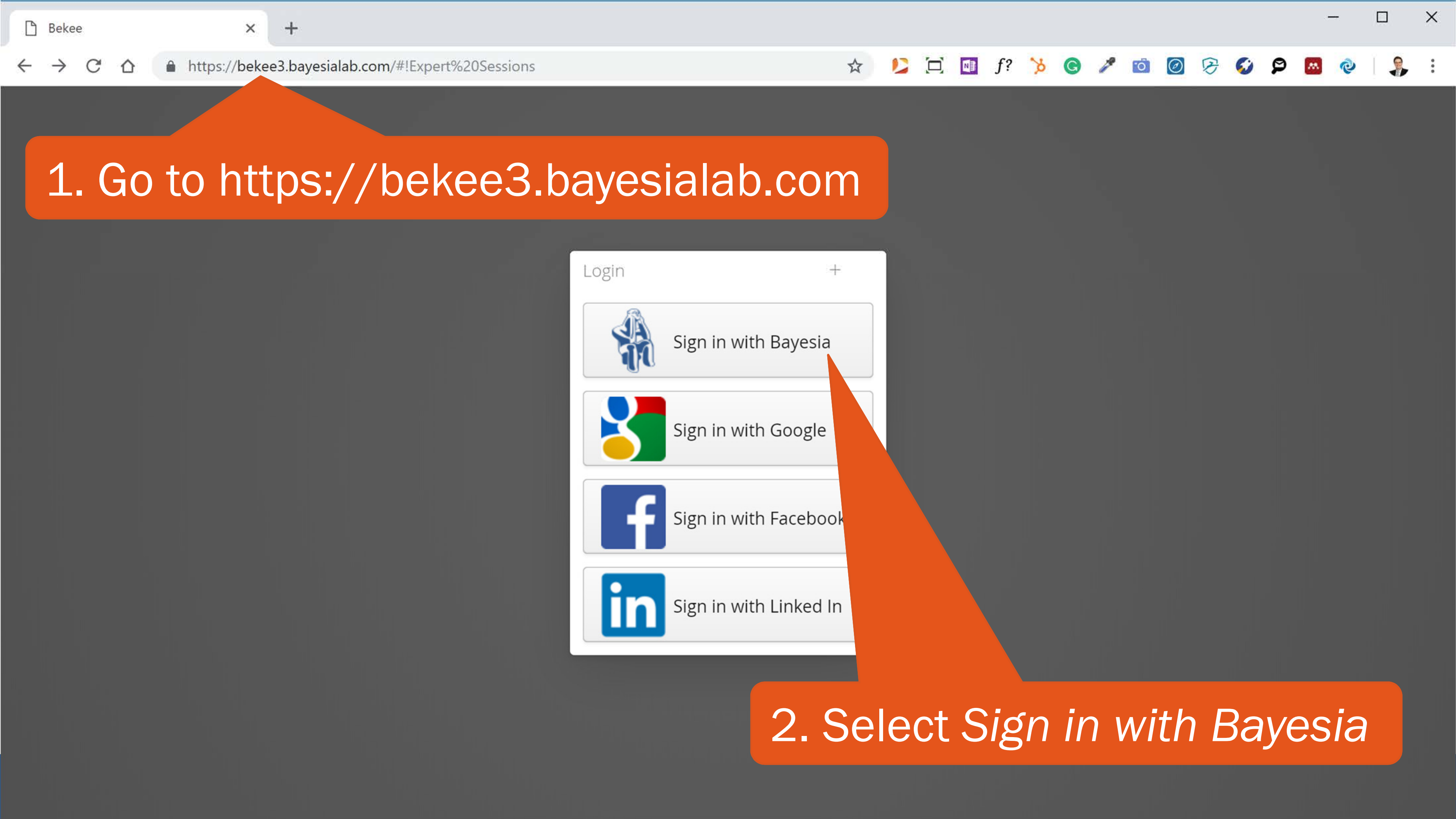
2. Knowledge Elicitation



2. Knowledge Elicitation

Assessment to be Performed:

PLA(N) Detection	Depth	Territory	No Action	Rescue	Capture/H...
False	<500m	Chinese Territorial Waters	100.000	0.000	0.000
		Chinese-Claimed Territorial Waters	100.000	0.000	0.000
		International Waters	100.000	0.000	0.000
	>500m	Chinese Territorial Waters	100.000	0.000	0.000
		Chinese-Claimed Territorial Waters	100.000	0.000	0.000
		International Waters	100.000	0.000	0.000
True	<500m	Chinese Territorial Waters	5.000	20.000	75.000
		Chinese-Claimed Territorial Waters	25.000	50.000	25.000
		International Waters	10.000	40.000	50.000
	>500m	Chinese Territorial Waters	100.000	0.000	0.000
		Chinese-Claimed Territorial Waters	100.000	0.000	0.000
		International Waters	100.000	0.000	0.000



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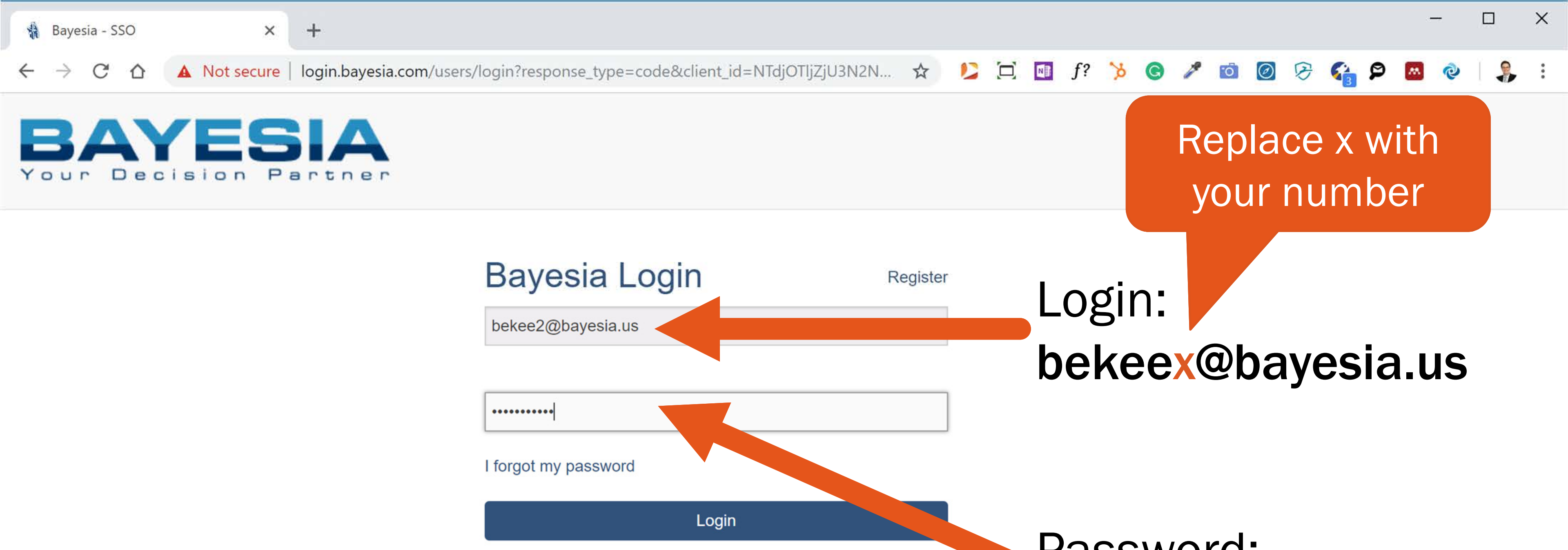

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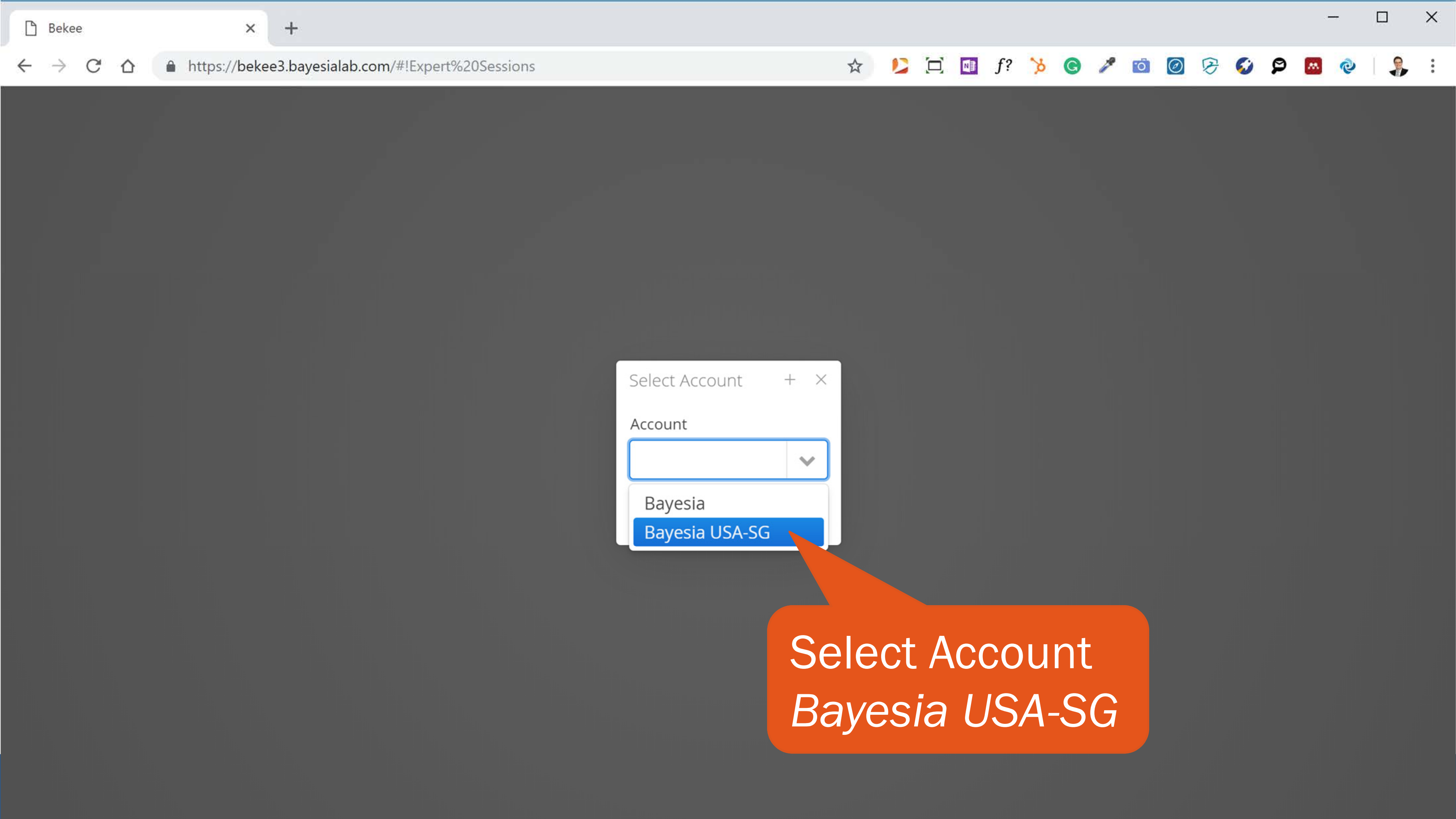
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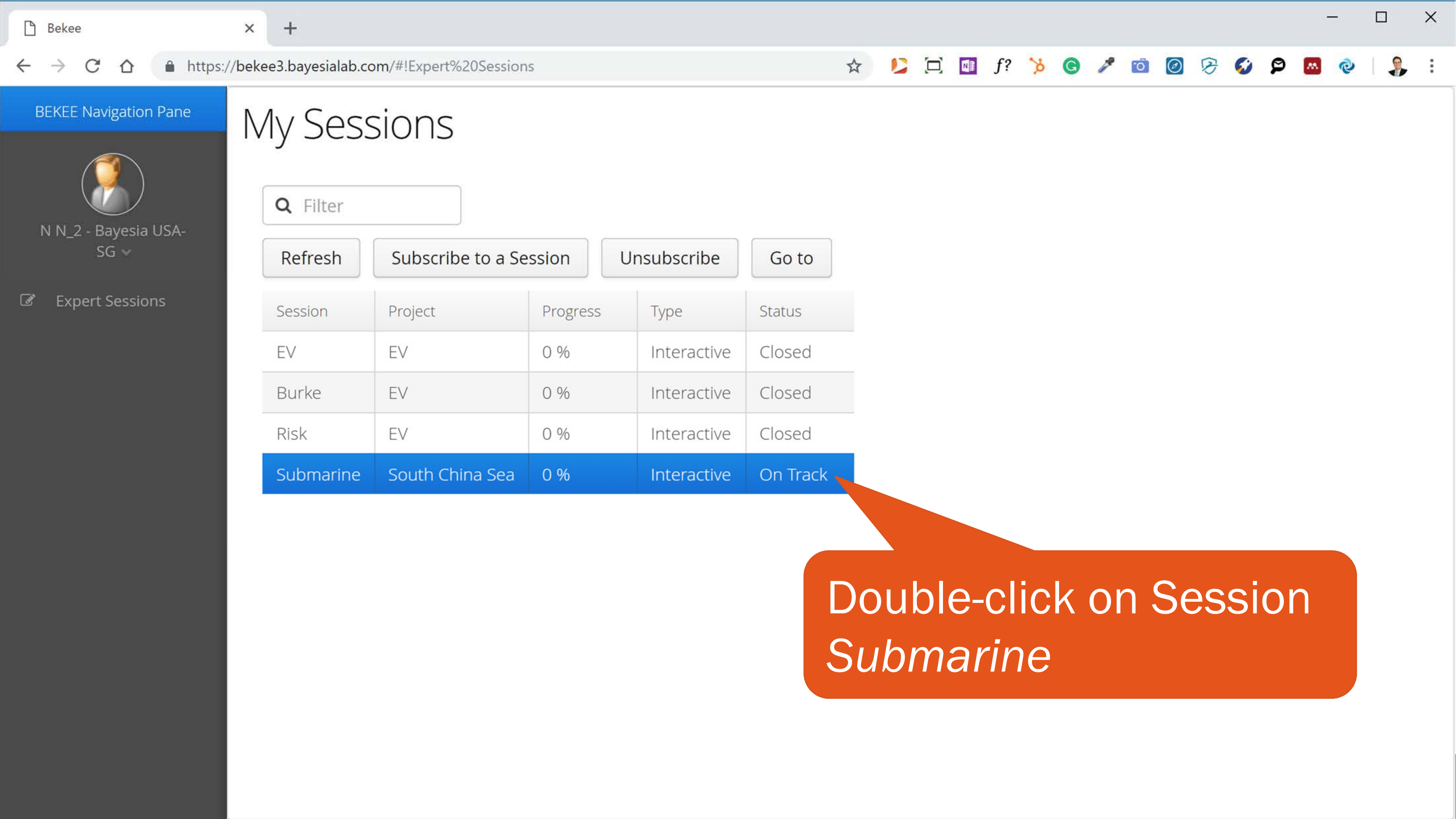
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Session | Project | Progress | Type | Status
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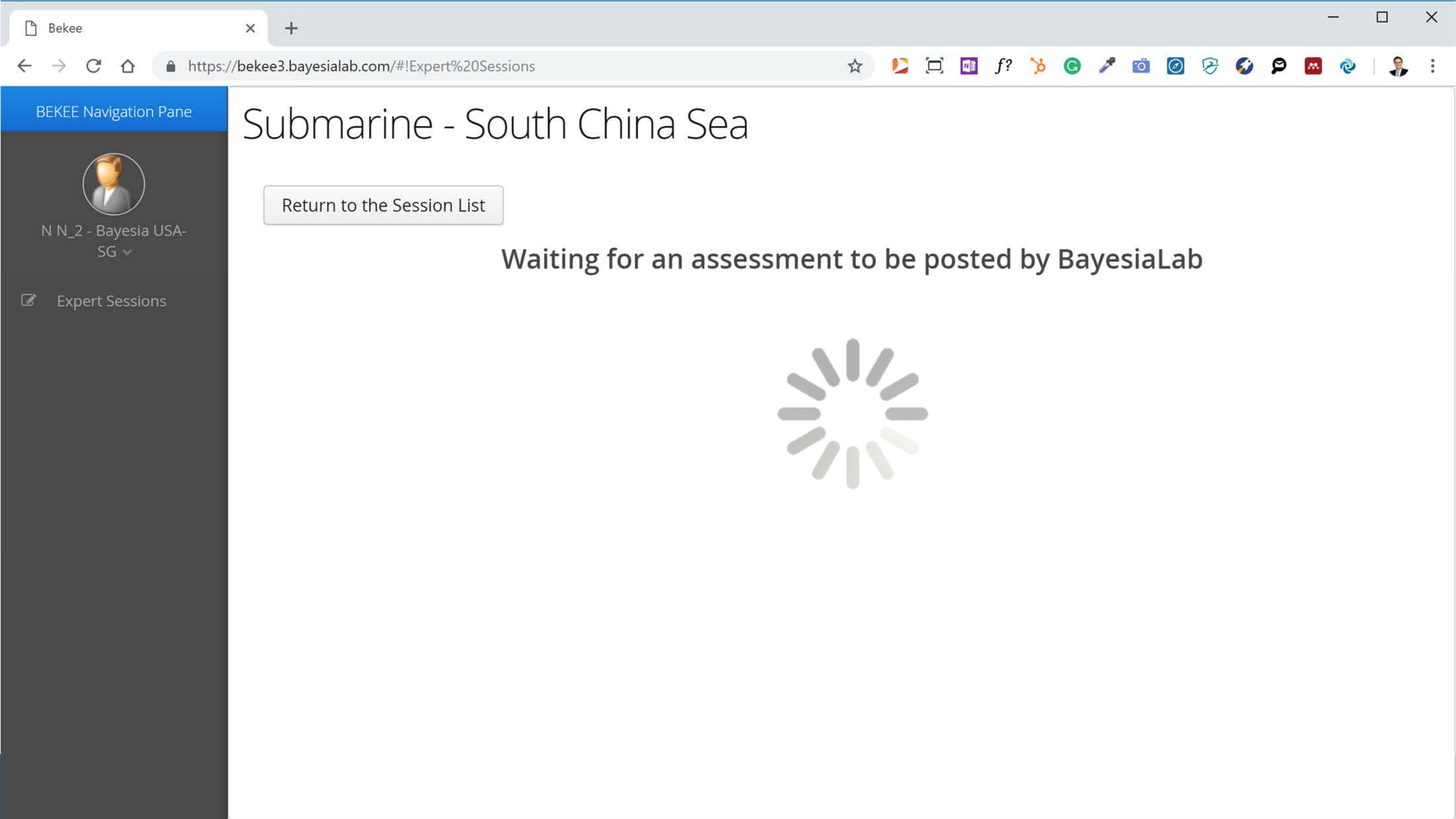
Burke | EV | 0 % | Interactive | Closed
Risk | EV | 0 % | Interactive | Closed
Submarine | South China Sea | 0 % | Interactive | On Track
Double-click on Session *Submarine*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Expert Sessions
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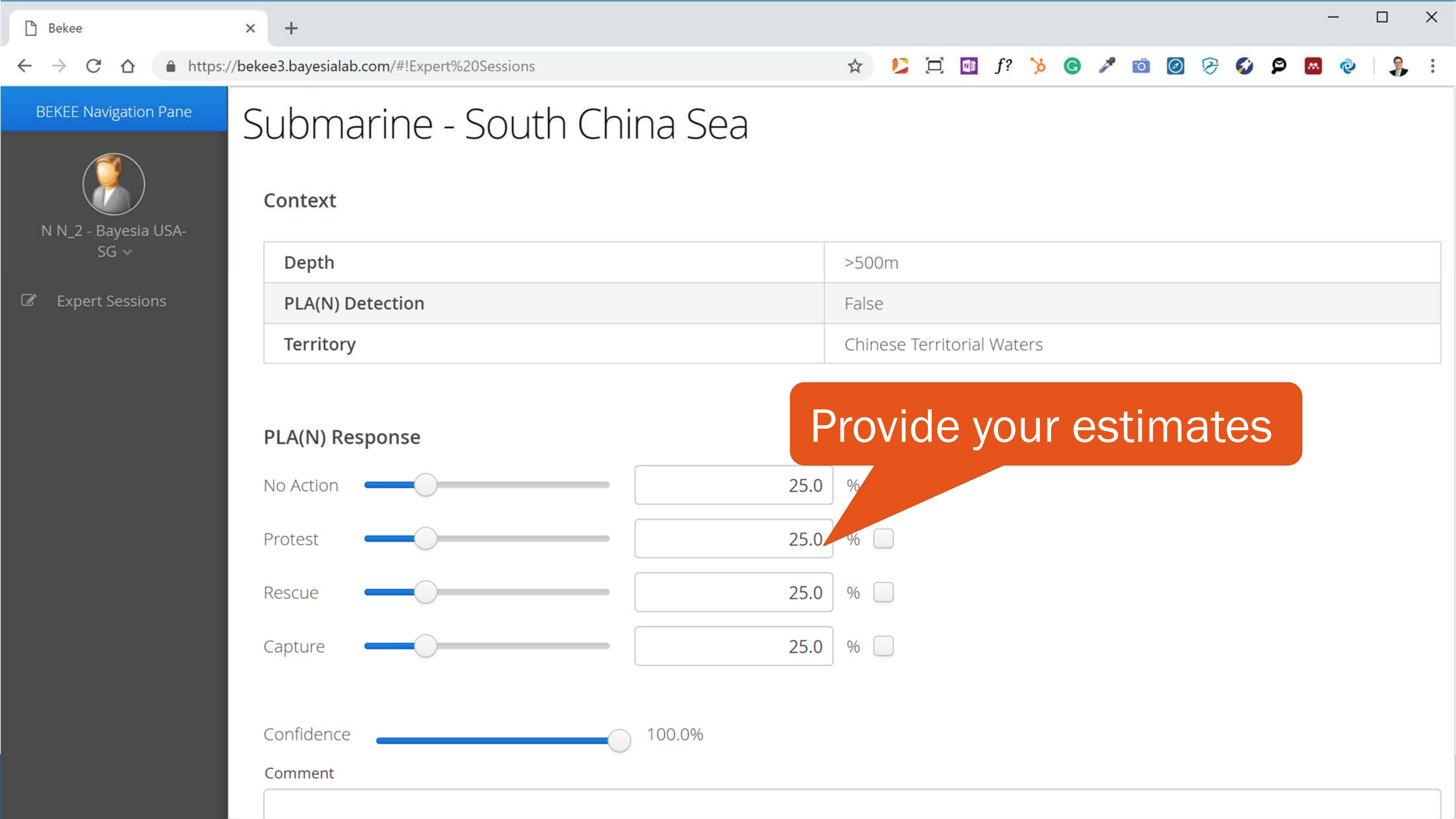
Waiting for an assessment to be posted by BayesiaLab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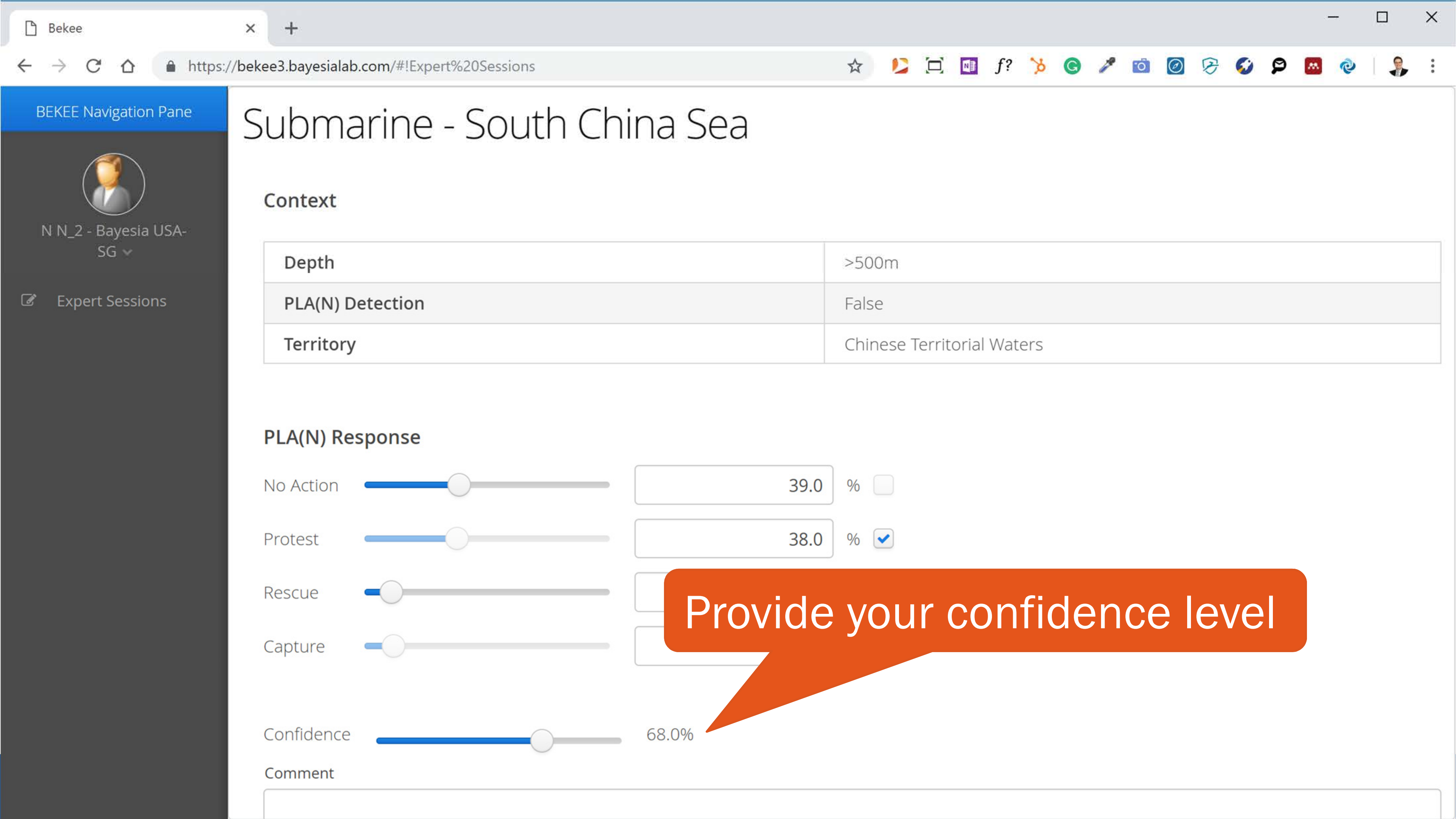
N N_2 - Bayesia USA-SG
Expert Sessions
Submarine - South China Sea
Context
Depth
>500m
PLA(N) Detection
False
Territory
Chinese Territorial Waters
PLA(N) Response
Provide your estimates
No Action
25.0
%
Protest
25.0
%
Rescue
25.0
%
Capture
25.0
%
Confidence
100.0%
Comment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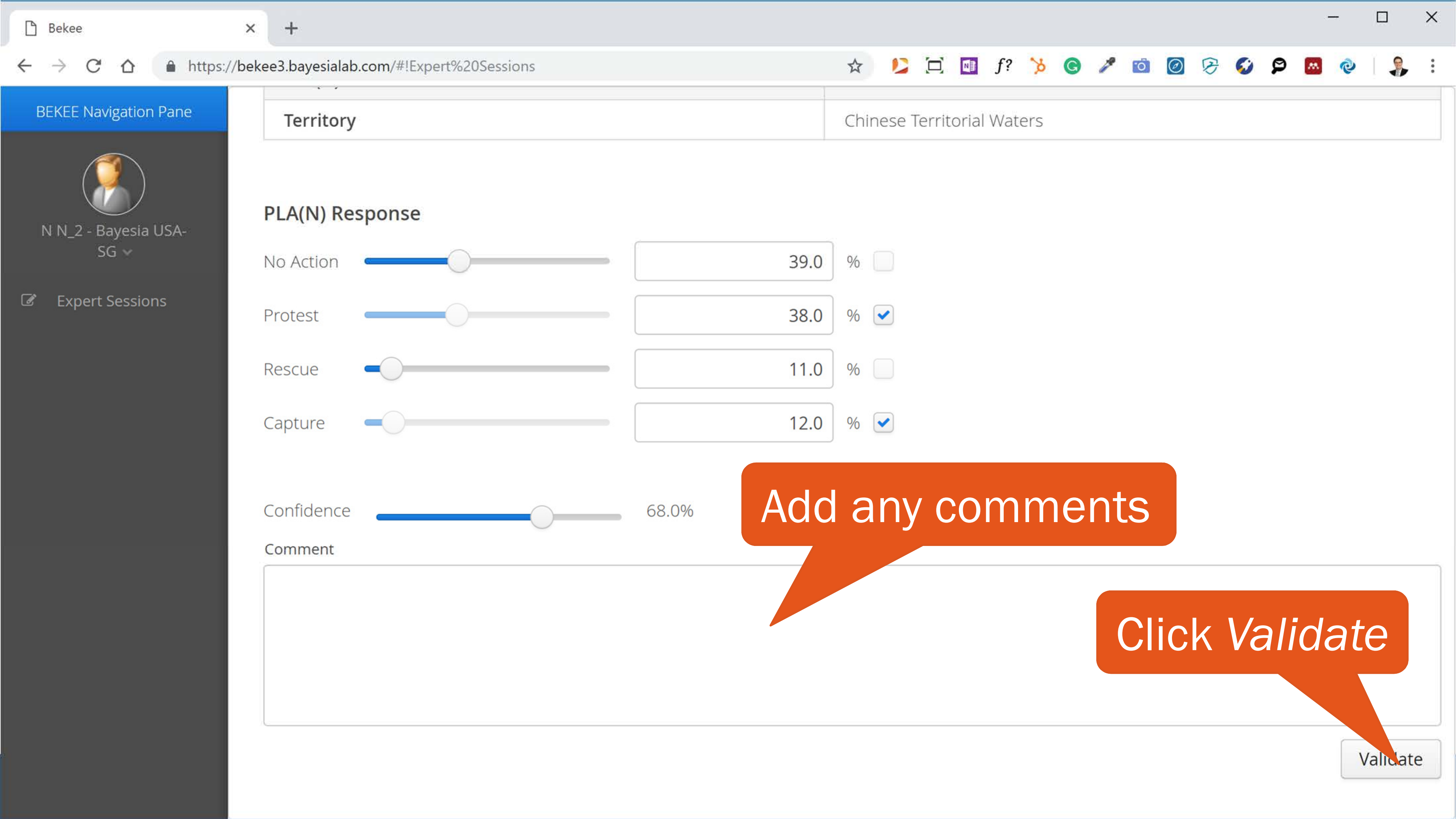
N N_2 - Bayesia USA-SG
Expert Sessions
Submarine - South China Sea
Context
Depth
>500m
PLA(N) Detection
False
Territory
Chinese Territorial Waters
PLA(N) Response
No Action
39.0
%
Protest
38.0
%
Rescue
Capture
Provide your confidence level
Confidence
68.0%
Comment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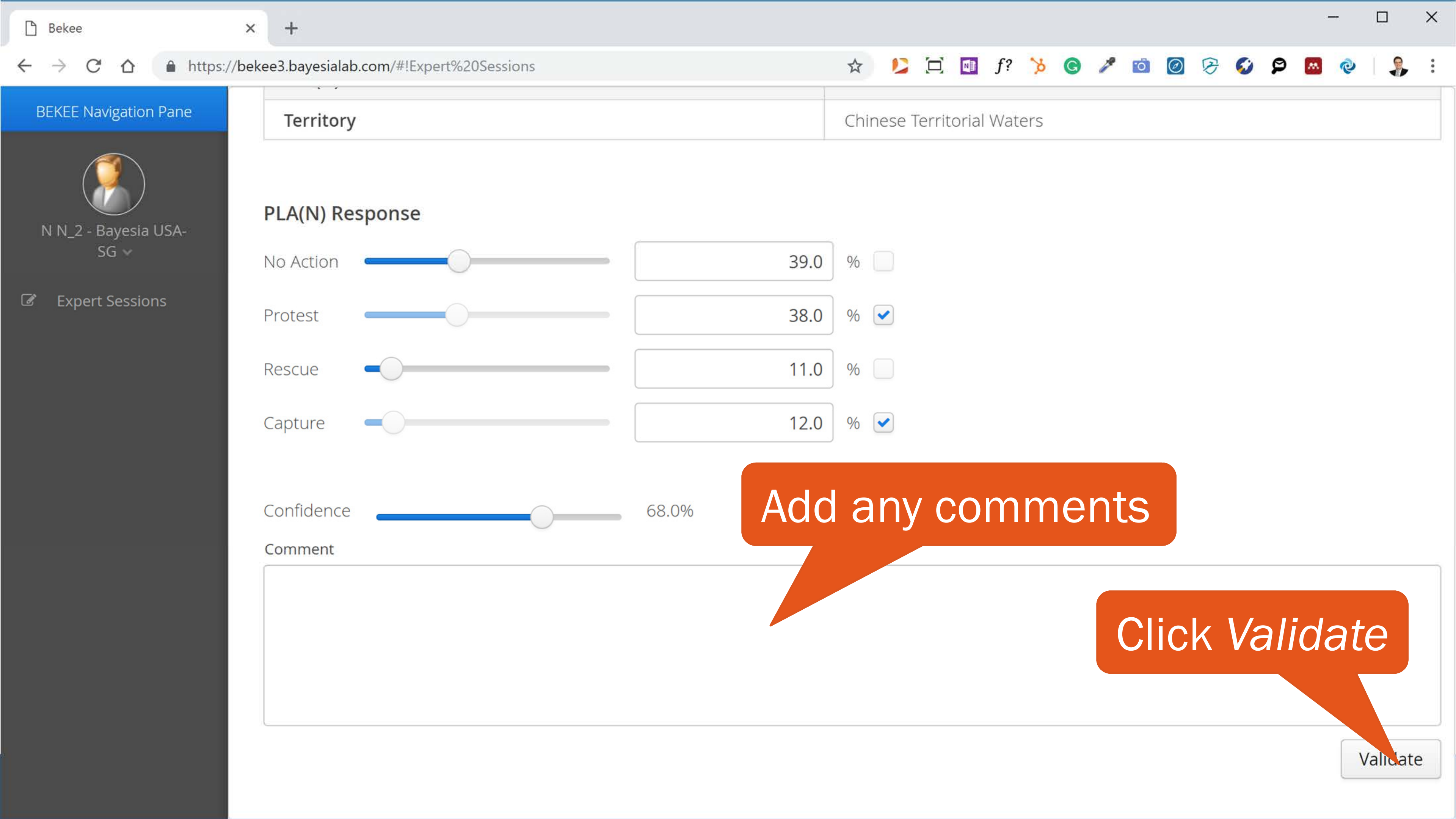
BEKEE Navigation Pane
N N_2 - Bayesia USA-SG
Expert Sessions
Territory
Chinese Territorial Waters
PLA(N) Response
No Action
39.0
%
Protest
38.0
%
Rescue
11.0
%
Capture
12.0
%
Confidence
68.0%
Comment
Add any comments
Click Validate
Validate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Expert Sessions
Territory
Chinese Territorial Waters
PLA(N) Response
No Action
39.0
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Protest
38.0
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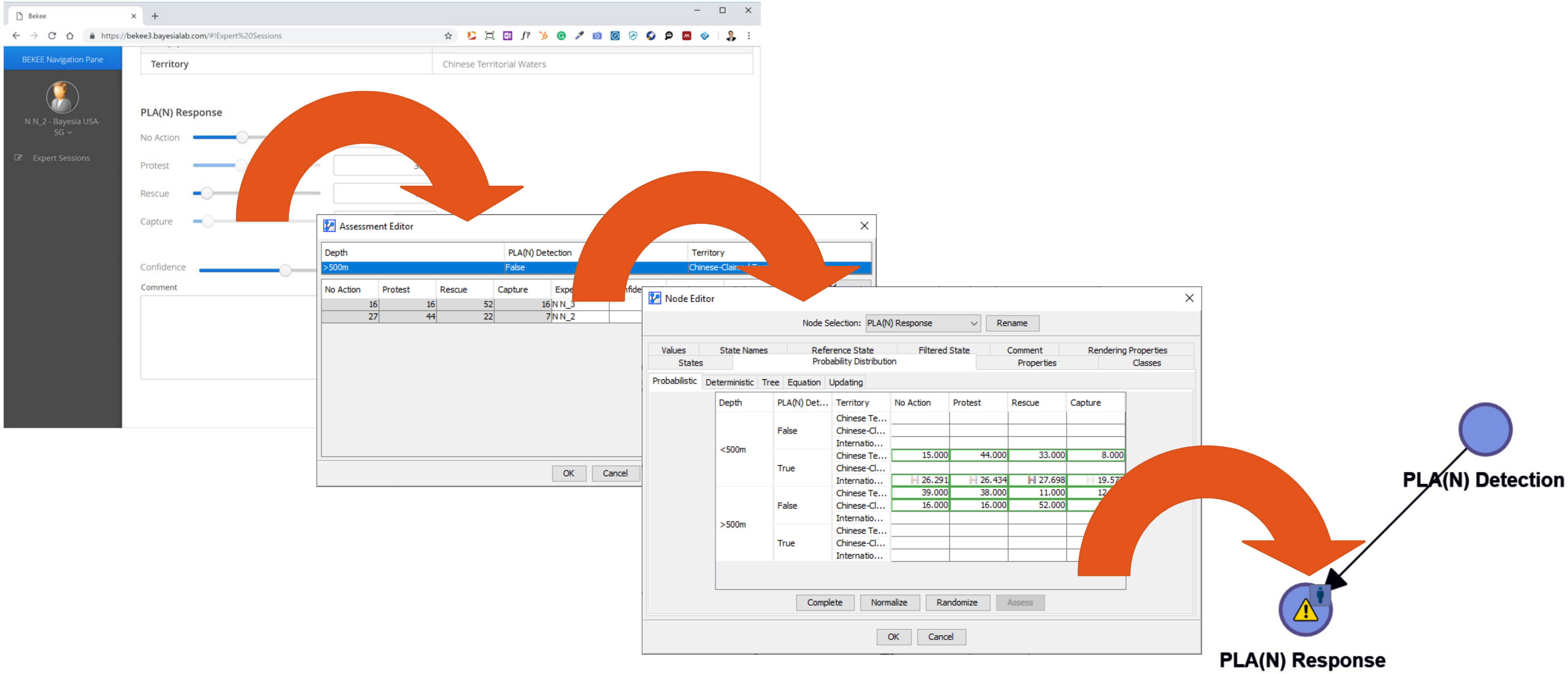
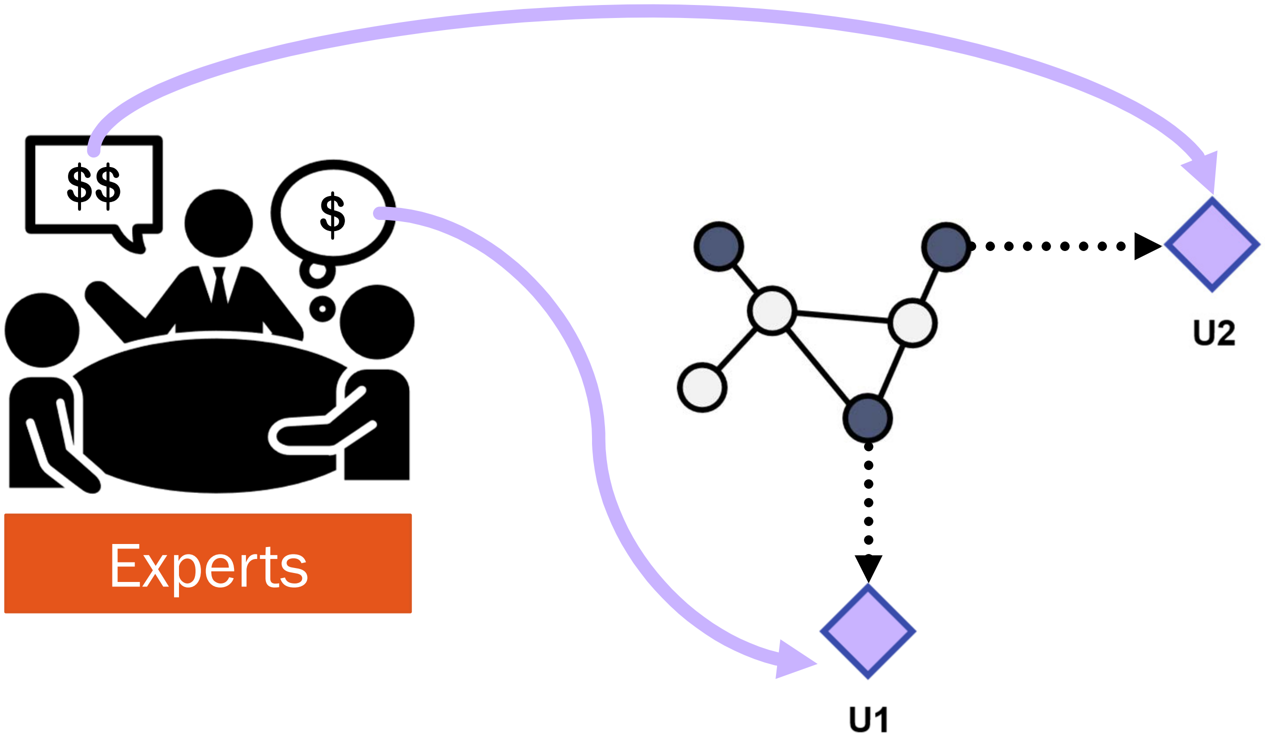
Rescue
11.0
%
Capture
12.0
%
Confidence
68.0%
Comment
Add any comments
Click *Validate*
Validate

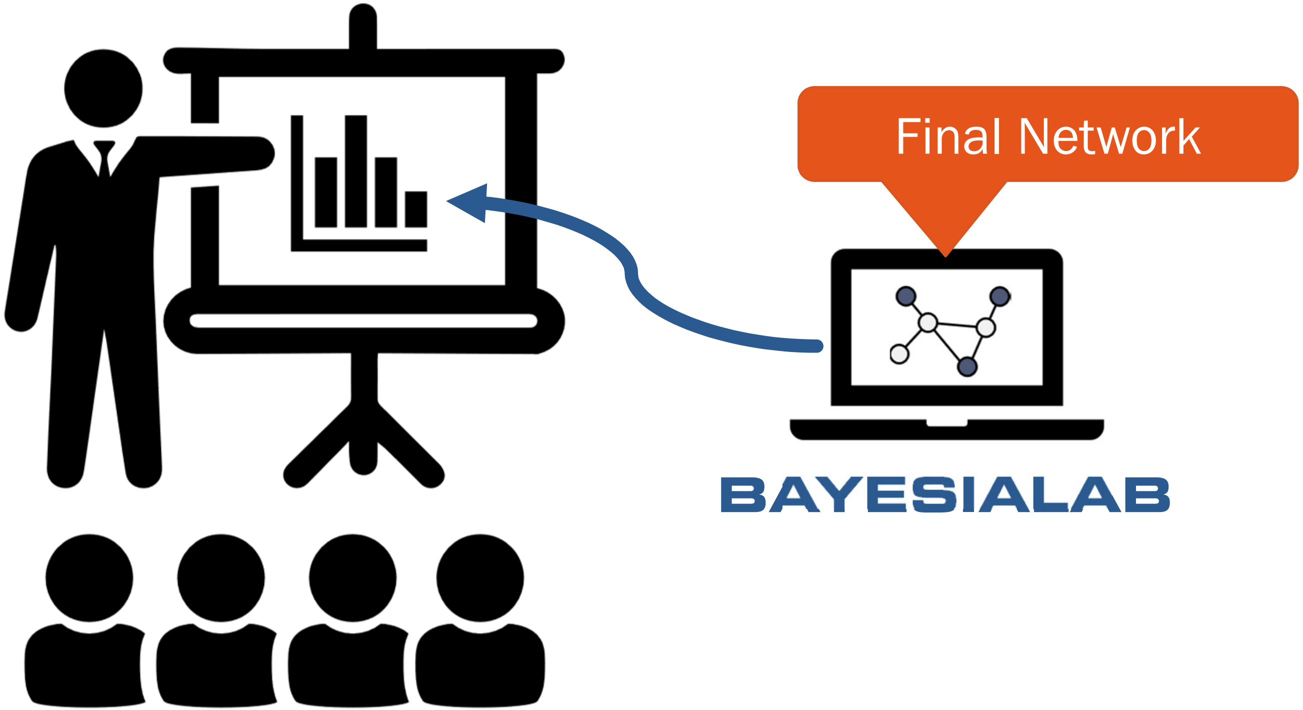
Knowledge Elicitation



3. Assignment of Cost, Values, and Utilities



4. Inference, Analysis, and Decision Optimization



Concluding Remarks

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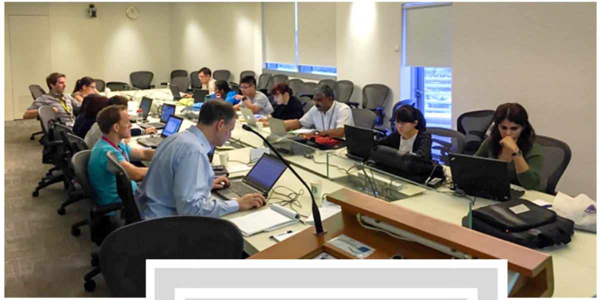
- March 19–21
  Washington, D.C.
- April 3–4
  Amsterdam
  Netherlands



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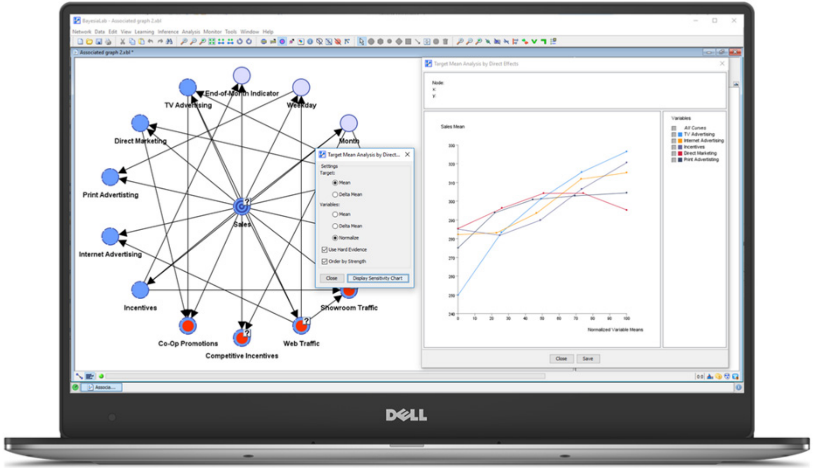

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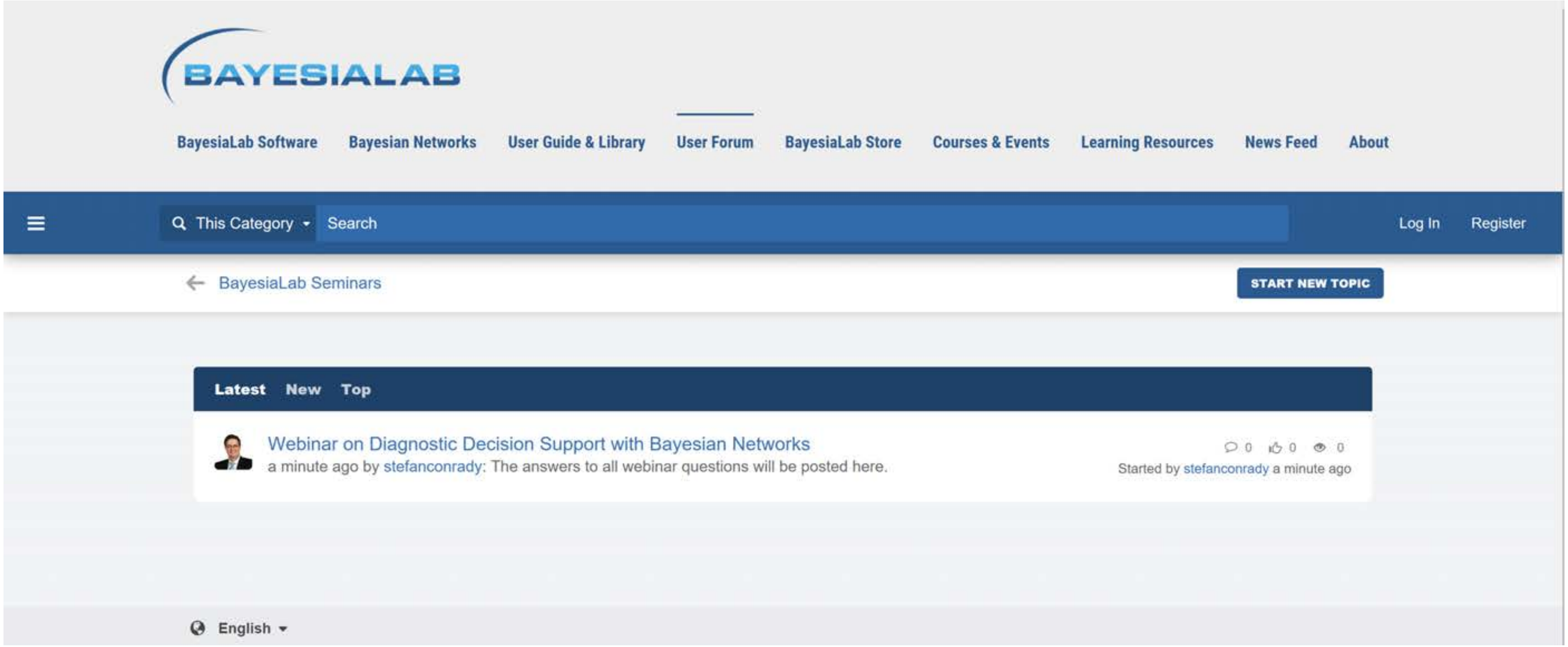


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